Characterizing changing landscape patterns in West Africa: an object based image analysis approach

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Table of Contents

Abstract

To effectively combat malaria and other mosquito-borne diseases it is important to know the habitat of their vector and whether it is changing through human influence. That is why it is useful to determine changes in the landscape. Therefore the land cover of two transects in West Africa at two different moments (1986 and 2013) was classified. Object Based Image Analysis (OBIA) was used as it is well-suited for detecting human influence. For the image segmentation a multi-resolution segmentation (MRS) approach was used. The classification was based on the spectral values, shape, relative position and border of the objects. Both transects showed a large increase in urban area (79% and 121%). In transect 1 all urban areas increased in size by 50 to 82%. However, in transect 2 only the main urban area increased in size, while the small urban areas present decreased in size by 7 to 74%. Transect 1 showed a large increase in dense vegetation, while transect 2 showed a radical decrease in dense vegetation. Combined with the different urban changes this points to a different development trajectory for the two transects. The most likely explanation is different economic growth in the region of the transects. Patch shape complexity for both transects decreased even when the total number of patches increased. This is an indication that human influence has increased. Developing a method to estimate human influence in an area proved not possible with the current data and the outliers present in it. However, there was a strong correlation (r = 0.77) between the total number of patches in the landscape (a measure of fragmentation) and the percentage of the landscape covered by urban area + bare soil, roads and grassy fields. The classification method developed for transect 1 was quite robust as few changes were needed to apply it to transect 2. To make full use of OBIA higher resolution images are required, because the 30m resolution of Landsat images was not enough to use shape in the segmentation process likely due to the small irregular fields that made up a large part of the landscape in the transects.

1. Introduction

Over the past decade the global fight against malaria has been remarkably successful. In the period of 2000-2012 an estimated 3.3 million lives were saved. In that same period, the mortality rate was reduced by 42% globally and by 49% in the World Health Organization (WHO) African region (defined as the entirety of Africa with the exclusion of North Africa and the Middle East). At the same time malaria incidence rates declined by 25% worldwide and by 31% in the African Region. This success is mostly owed to a global campaign by the WHO and other Non-Governmental Organizations (NGOs), in cooperation with dozens of countries where malaria is endemic. However, despite this success there were still an estimated 207 million cases of malaria in 2012 alone, resulting in an estimated 627,000 deaths. The majority of which took place in sub-Saharan Africa (table 1) (WHO, 2013).

Table 1. Estimated number of malaria cases and malaria deaths in 2012 (WHO, 2013).

	Estimated cases (millions)	Estimated deaths (thousands)
World	207	627
sub-Saharan Africa	173.7	577

Other diseases transmitted by mosquitoes, such as yellow fever and dengue fever, have not been pushed back by the effort against malaria. Dengue fever in particular has grown rapidly, with reports of a 30-fold increase in the period of 1960 to 2010. Part of this increase is likely due to an increase in incidence reporting. Still, there is a sharply increasing trend when this is taken into account (WHO, 2009). With an estimated 25,000 deaths a year and 2.5 billion people living in endemic areas, dengue fever is an important disease to keep under control (Gubler, 2010). Unfortunately as of yet there are no approved vaccines (Whitehorn and Farrar, 2010). Prevention comes down to reducing the number of bites from mosquitoes that transmit the disease. This can be done in two ways. The first method is by reducing the number of bites by protecting the skin, either through more clothing or mosquito nets. The second method of control is to reduce the number of mosquitoes, for example by destroying their breeding grounds (WHO, 2013). For many mosquito species their breeding ground is stagnant or slow-moving water. Destroying this type of breeding grounds can be done by either removing the stagnant water or by increasing its flow velocity. Another option is to add pesticides that kill the mosquitoes or their larvae, though there are drawbacks to this option. Most notable of these are health concerns and an increasing pesticide resistance among many mosquito species (Ferguson, 2010). It is also possible to introduce a biological agent to the breeding grounds. However, introducing new species to combat other species has not always gone according to plan in the past (WHO, 2013). There are also mosquito species that lay their eggs in moist soil. These are the so-called floodwater mosquitoes. Destroying their breeding grounds is difficult as these are often used for agriculture, raising livestock or are located in floodplains (NPS, 2014).

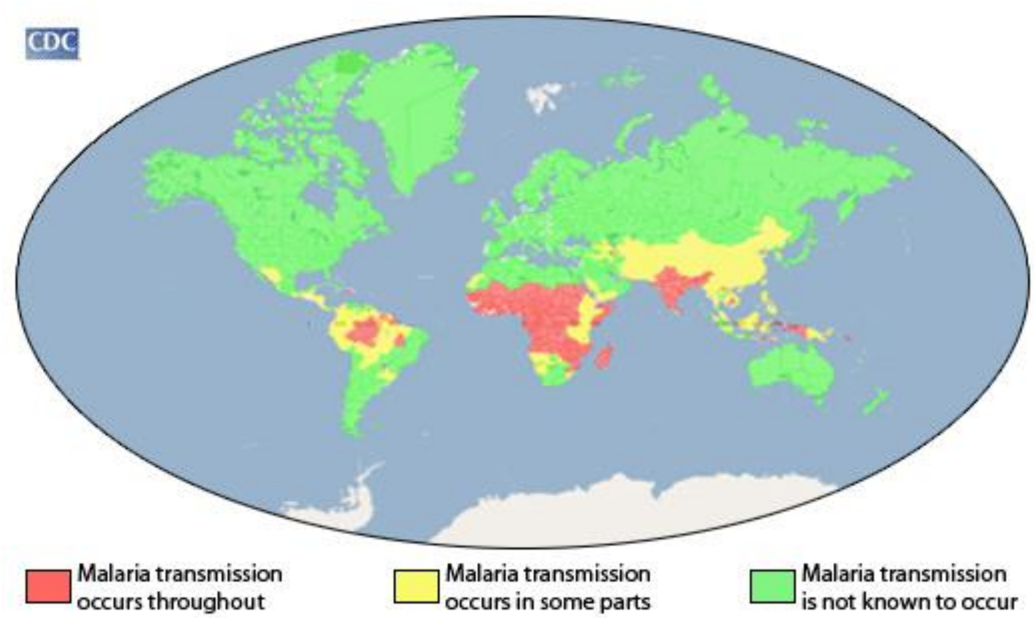

Figure 1. Approximation of where in the world malaria transmission takes place (CDC, 2014)

In many of the areas where malaria and other mosquito-borne diseases are endemic (figure 1), there has been a large increase in population and economic activity over the last decades, particularly in West Africa, defined as including the countries that are members of the Economic Community of West African States (ECOWAS). This trend is likely to continue for the foreseeable future. In 2010 an estimated 317 million people lived in West Africa, (figure 2) (ECOWAS, 2014). Population growth of the region is estimated at 2-2.5% per year and the total population is likely to exceed 400 million in 2020 and 500 million before 2035, with the bulk of this increase concentrated in Nigeria (CIA, 2014). This explosive population growth is coupled with some of the highest economic growth in the world. Nigeria for example has a yearly GDP growth of 7-10% according to the International Monetary Fund (IMF, 2014).

This rapid increase in population and economy will lead to an increase in urbanization. At the same time it will lead to a reduction in natural habitats due to logging or to clear space for housing, agriculture and industry. In general an increase in urbanization supports the breeding of various mosquito species (Whitehorn and Farrar, 2010). The destruction of natural habitats will lead to a more fragmented landscape where water management usually is an afterthought. Often this leads to more standing water and an increase in breeding grounds for mosquitoes (Norris, 2004). Therefore it is important to determine the human influence in a landscape and whether it is increasing or not. Human influence was defined as any land cover different than the land cover of the landscape in its natural state (without human influence). It was assumed that the natural state of the landscape in West Africa was dense vegetation and water. This assumption was based on the land cover of the forest reserves in the area. These reserves all have a land cover that is close to 100% dense vegetation and have seen little to no human influence for at least 25 years. The rivers that flow in the current landscape are also natural and have seen little human interference.

Figure 2. West Africa, defined as the countries member of ECOWAS (ECOWAS, 2014).

To effectively combat mosquito-borne diseases it is important to know the habitat of the mosquitoes (Ferguson, 2010). By using remote sensing it is possible to get just that: a fairly accurate overview of land cover in an area and through that the likely habitat of mosquitoes. Remote sensing methods are especially useful for remote areas for which little or no official data is available (Ademiluyi et al., 2008). It is important to know what the trend is over time for the landscape in an area. Is there an increase in urbanization? Is the area becoming more densely populated or is there a large urban sprawl? Is the landscape becoming more fragmented? These are the type of questions that need to be answered to get an idea of how the landscape is changing and how this will influence the habitat of the mosquito and the number of people at risk (Norris, 2004). After the changing landscape has been characterized in an area and it has been coupled to an increase in mosquito-borne diseases, it might be possible to detect a similar land cover trend in another area where such an increase in diseases has not yet occurred. This would give health organizations and (local) governments more time to implement measures. Measures to reverse the trend, or when that is not feasible, to increase preventive measures in the area and possibly save lives.

To characterize a changing landscape and to detect trends, the land cover has to be classified. One of the most common methods used for this is remote sensing with land cover classification on a per pixel basis. However, recently developed methods do not only look at individual pixels, but they try to group similar pixels together, based on their spectral profile, as well as their shape and in some cases adjacency to other objects. This is more similar to how humans look at images and should, in theory, lead to better results than a pixel-based approach (Blaschke, 2010). This Object Based Image Analysis (OBIA) approach will be further explained in chapter 3.

The aim of this study is twofold:

- To compare landscape patterns along two transects in West Africa and their changes through time and space. One transect is located approximately 100km inland, while the other transect is located 300km inland. Both transects contain highly urbanized areas and heavily forested natural areas.
- To determine to what extent it is possible to use landscape patterns to estimate human influence in an area.

Research questions:

- What trends can be seen in the spatial patterns in the two transects through time and space?
- What differences can be seen in the spatial patterns when comparing the two transects? Do these differences change over time?
- How can landscape patterns be used to estimate the human influence in an area?

2. Landscape Ecology

2.1. Introduction to landscape ecology

To be able to characterize the landscape and determine the landscape patterns it is necessary to give an overview of landscape ecology, as this is the scientific field that deals with this topic. To understand the field of landscape ecology it is important to define what a landscape is. The term landscape has acquired various connotations over time (Wu, 2007). Even within the field of landscape ecology there are numerous definitions based on the subject being studied. A very broad definition of landscape is as follows: “A geographic area in which variables of interest are spatially heterogeneous. The boundary of a landscape may be delineated based on geographic, ecological, or administrative units (e.g., a watershed, an urban area, or a county) which are relevant to the research questions and objectives” (Wu, 2007). The size of a landscape that is being studied varies highly based on the research that is being done. For example, studying the effect of vegetation on the movement patterns of beetles would not require the study of a landscape of tens of square kilometres (Wiens and Milne, 1989).

The term landscape ecology was already used in the 1930s. However, it took until the 1980s before it was recognized as a viable scientific field, because the advent of remote sensing and the rapidly increasing computing power of computers made it possible to study landscape patterns in-depth (Wu and Hobbs, 2007).

Landscape ecology is based on the concept that there is a (strong) relationship between spatial patterns and ecological processes. It is the science of studying these relationships on different scales and organizational levels. Often it has a focus on broad ecological and environmental issues. It is a highly interdisciplinary field that combines various natural sciences and increasingly social sciences as well (Wu, 2007). The latter is particularly true when dealing with large-scale landscapes with increasing human influence. As well as research dealing with sustainability (Wu, 2006, Naveh, 2007).

2.2. Landscape patterns

2.2.1. The importance of landscape patterns

Large-scale analyses of a landscape will never be able to replace the need to understand the small-scale processes that take place within that landscape. Nevertheless it is an important topic. Large-scale spatial changes, such as urbanization and deforestation, can have a large effect on the entire landscape (O'Neill et al., 1986). An example is that fragmentation of the landscape can cause the complete collapse of ecosystems, because the recovery rate can be severely impacted due to a lowered dispersion rate of pioneer species (Gardner et al., 1993). To that end it is important to study landscape patterns. The change in landscape patterns in particular can give information on, for example, ecosystem health (Riiters et al., 1997) and water quality (Hunsaker et al., 1992).

2.2.2. Quantifying landscape patterns

Every landscape contains complex spatial patterns, varying over time and space. To compare different landscapes and identify significant changes over time in these spatial patterns, quantitative methods have to be used (Turner, 1989). This is why measuring, analysing and interpreting spatial patterns receives a lot of attention in landscape ecology (Haines-Young and Chopping, 1996). The way these spatial patterns are quantified depends on what data was collected, how it was collected and what the objectives of the study are (McGarigal, 2014).

To aid in quantifying the landscape patterns a large number of landscape metrics have been developed. Most of these landscape metrics are indices developed for categorical map patterns, as a lot of research in landscape ecology is focused on categorical map patterns. These indices characterize the landscape, or refer to a combination of attributes that are important for the subject that is being studied. Usually this subject is a particular type of species (Uuema et al., 2009). There are three different types of metrics: patch, class and landscape metrics. Metrics are calculated for every patch, class and landscape respectively. There are two main components of landscape patterns. The first is composition which deals with the variety and the relative abundance of the various classes present in the landscape. The second is configuration which deals with the (relative) distribution of patches in the landscape, as well as the spatial character of the patches such as shape (Li and Wu, 2004, McGarigal, 2014).

2.2.3. Landscape pattern analysis issues

There are three general types of issues regarding landscape pattern analysis. First there are inherent limitations of landscape indices. Often there are variable responses to changes in spatial patterns. This makes it difficult to interpret the results of landscape indices (Li and Wu, 2004). Second there are conceptual flaws in landscape pattern analysis. This can lead to the following issues: unwarranted relationships between patterns and processes; the use of landscape indices that are ecologically irrelevant and confusion on the scale of observation and analysis (Li and Wu, 2004). Finally there is the misuse of landscape indices. For example: quantification of patterns without regard to the processes; inference from a single landscape to other, inappropriate, landscapes. As well as using a larger number of indices than necessary (Li and Wu, 2004). The latter in particular is often the case as there are still only two major components to describe landscape patterns, composition and configuration (Li and Wu, 2004, McGarigal, 2014).

2.3. Remote sensing in landscape ecology

Over the past decades landscape ecology studies have increasingly started using data obtained through remote sensing. The development of landscape ecology has been significantly stimulated by advancements in the fields of remote sensing and GIS (Newton et al., 2009). A review by Newton et al. (2009) of 438 research papers published in Landscape Ecology (the foremost journal in the field) between 2004 and 2008 showed that 36% of the studies explicitly mentioned remote sensing. However, while almost two-thirds of the studies did not mention using remote sensing methods it is likely that many of those still used information derived from remote sensing (Newton et al., 2009).

The applications of remote sensing data in landscape ecology range from monitoring biodiversity and species richness, to land use change assessments and the quantification of carbon fluxes.

As the field of remote sensing has matured the methods used have become more advanced. For example, land cover maps derived from remote sensing data traditionally showed a variety of land cover classes. This general mapping of classes required a large amount of ground truth data to make sure that the classification was done correctly. However, in recent years researchers have started using targeted mapping. In many studies only a single class is of interest, for example when mapping a rare or invasive species (Boyd and Foody, 2011). In these cases it is far more efficient to ensure the classification of the class of interest is optimal (Weiers et al., 2004, Boyd and Foody, 2011). For this research, however, more than one land cover class will be of interest as a distinction needs to be made between human influenced and natural land cover. Another interesting development is the increasing use of airborne laser scanning (ALS) in for example: forest inventory research, biomass assessment and bird species richness (Boyd and Foody, 2011).

The latest development in remote sensing is Object Based Image Analysis (OBIA). This has been described as a new paradigm or scientific revolution by Blaschke, et al. (2014). Its current use in landscape ecology is limited. However, based on the speed of the developments and the increasing amount of OBIA research within the remote sensing field (see chapter 3.5) it is likely that this will change over the next few years.

Already there is some recent research using OBIA within landscape ecology. For example research by Hagenlocher, et al. (2014) uses OBIA to model hotspots of climate change in the Sahel based on geo-spatial datasets, including remote sensing data. Another example is the use of OBIA to map geomorphic and ecological zones on coral reefs by Phinn, et al. (2012). Or applying OBIA and data mining to a Landsat time-series to map sugarcane over large areas as was done by Vieira, et al. (2012).

OBIA is well-suited for anthropogenic change detection, because anthropogenic objects (for example buildings and roads) are generally more homogeneous and have distinct boundaries. This in contrast to most natural objects (Chen et al., 2012). A goal of this research is to devise a method to predict human influence based on the landscape patterns. Therefore OBIA is deemed to be the best method to use for characterizing the landscape for this research.

3. Object Based Image Analysis

3.1. Introduction to object based image analysis

Object Based Image Analysis (OBIA) is also called Geospatial Object Based Image Analysis (GEOBIA) when dealing with objects on the earth's surface. It is a sub-discipline of GIScience dealing with partitioning remote sensing images into image-objects and characterizing them at a spatial, spectral and temporal scale (Hay and Castilla, 2006). OBIA builds on concepts that have been used in remote sensing image analysis for decades, such as feature extraction, segmentation and edge-detection. Still it is a critical new part that bridges the gap between multi-scale landscape analysis, Geographic Information Systems (GIS), GIScience and Earth Observation (Blaschke, 2010).

OBIA only started to emerge as a viable part of remote sensing in the late 1990's when two trends combined, the increasing availability of high resolution imagery, as well as powerful offthe-shelf software that combines image processing and GIS in a single, object based environment (Blaschke, 2010). The advantage of OBIA over pixel-based analysis is that it provides true geographical objects. It also incorporates spatial photo-interpretive elements (e.g. texture, context, shape), and with that it can cope with the increased variability that comes with the ever increasing resolution of remote sensing imagery. The main objective of OBIA is to develop the theory, methods and tools that are needed to replicate, or improve upon, human interpretation of remote sensing images. This should be done in a (semi-)automated fashion that will improve repeatability, while reducing subjectivity, labour and time (Hay and Castilla, 2006).

It is assumed that OBIA can identify objects in remote sensing images that are related to real objects in the landscape. To this end an image is first partitioned into a set of regions that are uniform within themselves when compared to neighbouring regions (Castilla and Hay, 2008). This is based on one or more criteria of homogeneity in one or more dimension. This means that these regions will have more spectral information when compared to a single pixel (for example: mean values and variance instead of a single value) (Blaschke, 2010). These regions, also called segments, are later linked to landscape objects through object-based classification (Castilla and Hay, 2008).

3.2. OBIA advantages and disadvantages

3.2.1. Advantages

OBIA partitions an image into objects exhibiting useful features (e.g. shape, texture, context relation to other objects in the vicinity). This is similar to how humans organize what they see, thus making interpretation easier. Using image-objects reduces the computational load compared to a pixel-based approach and also enables the user to take advantage of complex techniques (e.g. non-parametric techniques).

A problem that is often encountered in remote sensing is the modifiable areal unit problem (MAUP) (Hay and Castilla, 2006). The problem is that boundaries of zones are often arbitrary. Changing the boundaries of a zone can also have an effect on the results of the analysis. This gives rise to the MAUP (Jelinski and Wu, 1996). An image object based approach is less sensitive to this problem than a pixel based approach (Hay and Castilla, 2006).

3.2.2. Disadvantages

Processing large datasets still poses challenges, even when using OBIA. Segmentation has no unique solution; a change in parameters can lead to different segmentations. This is unlikely to be ever solved, as even human interpreters will not identify exactly the same objects. There is no consensus on the conceptual foundations of OBIA (the relationship between image-objects (segments) and landscape objects (patches). For example, how do you know when your segmentation is good? Scale and hierarchical relations are also poorly understood. For example do segments at coarse resolutions really emerge or evolve from segments at a finer resolution and should boundaries overlap at different scales? If yes, is there an ecological basis for this (Hay and Castilla, 2006)? Is it even possible to classify everything as an object in the first place? For example, is a forest an object or a continuous transition from few to many trees per areal unit?

OBIA relies on expert knowledge of the user. Essentially it is a computer-aided photo-interpretation process, where two users will not obtain the same results as their experience differs (Arvor et al., 2013). The processing chain is also not entirely controlled and documented. For example the segmentation process is based on parameters that make it hard to justify choices. Because of these last two issues OBIA methods are rarely transferrable (Arvor et al., 2013).

3.3. OBIA methods

There are a number of different approaches to OBIA. Most notably among those are the Fractal Net Evolution Approach (FNEA), Linear Scale-Space and Blob-Feature Detection (SS) and Multi-Resolution Segmentation (MRS). As the multi-resolution segmentation approach is most commonly used in landscape ecology this will be the method used for this research. The following will give a short overview of the MRS method.

3.3.1. Multi-Resolution Segmentation (MRS)

MRS is a region-based technique that is regarded as the most successful segmentation method for many remote sensing applications (Witharana and Civco, 2014). Scale, shape and compactness are the main parameters. MRS starts with each pixel forming one image object. At every next step a pair of these image objects is merged into a single larger object. This merging is based on local homogeneity criteria that describe the similarity of adjacent image objects. This is not a 'fit' or 'no fit' criterion, but a cost is assigned to every merge that depends on the "degree of fitting'. This degree of fitting is compared to a 'least degree of fitting' parameter set by the user and the image objects are merged based on this. The higher the 'least degree of fitting' the larger the resulting image objects will be as more merges will be permitted. Therefore the 'least degree of fitting' is seen as the scale parameter (Baatz and Schäpe, 2000).

The scale parameter is an important parameter in multi-resolution segmentation as it determines what level of heterogeneity is allowed in the segmentation process. This directly determines the size of the created image objects (Rahman and Saha, 2008, Witharana and Civco, 2014). The image objects created in this way not only contain the information of the pixels they are made up of, but information on texture, shape and their relative position to other image objects can also be extracted (Ambiente, 2000).

The homogeneity criteria is a combination of spectral values (wavelength) and shape. By changing the relative weights of these two components the influence of either on the creation of image objects can be adjusted. When shape is used in the segmentation the shape of the objects can be adjusted by changing their compactness and its counterpart smoothness. A high compactness leads to more compact (fringed) image objects, while a high smoothness leads to more smooth (rounded) image objects (Rahman and Saha, 2008). The approach used in this research does not take shape into account (set to zero) as it did not improve the results of the segmentation (see 4.2).

3.3.1.1. Advantages

Unique spatial measures of an image object are defined in the MRS approach. By weighing these spatial measures it is possible to upscale objects within an image. This reduces the MAUP effect (Hay et al., 2003). The underlying concepts are conceptually simple and are based on strong empirical evidence (Hay et al., 2003). No a priori image information is required according to Hay et al., 2003. However, knowing the typical size of the objects being studied will improve the results. The relationship between pixel size and image-objects is taken into account. This means that at fine scales the results closely resemble known image-objects (Hay et al., 2003). Object-specific data sets have been proven to improve land-cover classification (Hay et al., 2003).

3.3.1.2. Disadvantages

Object modelling is done empirically. So results have to be validated against field data, but this is not always possible (Hay et al., 2003). Finding optimal parameter values often takes a trial-and-error approach. This approach is subjective and takes up time (Hay et al., 2003). There is no full reproducibility as the borders of low contrast image objects can be arbitrary (Baatz and Schäpe, 2000). Linking objects through scale reduces the MAUP, however, there is no ecological theory that supports this practice (Hay et al., 2003).

3.4. OBIA and landscape ecology

The use of OBIA in landscape ecology is still limited. This is especially true for West Africa, because only a single paper that used OBIA in West Africa was found. No mention of OBIA was found in an overview paper “Remote sensing and the future of landscape ecology” by Newton, et al. (2009). Here 438 papers published in *Landscape Ecology* in the years 2004-2008 were analysed for use of remote sensing. The conclusions were that only 36% mentioned remote sensing. 46% of those used aerial photographs and 42% Landsat imagery. Remote sensing was almost exclusively used for thematic mapping. This is a rather limited use of a potentially valuable tool. 75% of the studies mentioning remote sensing did not give any measure of error or uncertainty (Newton et al., 2009). The overview paper by Blaschke (2010) on object based image analysis for remote sensing only mentions landscape ecology once. Only two of the reviewed papers were published in Landscape Ecology, the main landscape ecology journal. However, a number of the papers mentioned do have a (direct) link with landscape ecology. For example: in six different papers OBIA methods are used to link the obtained objects to patches in landscape ecology (Blaschke, 2010). The study further found that OBIA was frequently used in forestry and vegetation inventorying. For example studies by Xie, et al. (2008), Chubey, et al. (2006) and Maier, et al. (2008) all deal with forest inventorying (Blaschke, 2010).

3.5. Current use of OBIA in Africa

The overview papers by Newton, et al. (2009) and Blaschke (2010) are five and four years old respectively. As OBIA is a fairly new development in remote sensing it is likely that newer researches use OBIA more often. Therefore it would be useful to get a more up-to-date overview of current OBIA use. To that end the number of papers that mentioned OBIA versus the number that mentioned remote sensing in the title or abstract during 2011-2014 in the earth and planetary sciences field were counted using Scopus (table 2).

*Table 2. Papers in Scopus that mentioned remote sensing or OBIA worldwide, compared to Africa from 2011-2014 in the Earth and Planetary Sciences field. *The OBIA search term was as follows: object-based OR obia OR geobia OR definiens OR object-oriented (10-10-2014).*

Search term	Papers
"remote sensing"	8877
OBIA*	870
"remote sensing" AND Africa	848
OBIA* AND Africa	12

As can be seen from the results (table 2) the amount of OBIA research in the earth and planetary sciences field has become significant. Currently for every 10 papers that mention remote sensing in the abstract there is one that mentions OBIA. However, this is only the case when looking worldwide. Only 12 papers mentioned OBIA and Africa in the abstract from 2011-2014. While in the same period 848 papers were found that mentioned remote sensing and Africa in the abstract. The results show that there is little OBIA research in Africa.

3.6. Review of landscape ecology research in West Africa

A lot of the landscape ecology research in West Africa is done by local researchers (see *Mengistu and Salami, 2007, Ademiluyi et al., 2008, Akinyemi, 2013* and *Obiefuna et al., 2013*). The advantage of this is that they have more local knowledge. This should lead to better research results. However, there are also some problems with this. Most of the research being done is not very in-depth and uses fairly simple methods, perhaps due to a lack of resources. There is little to no mention of uncertainties or errors present in the remote sensing data or methods used to obtain results (though there are exceptions, see *Akinyemi, 2013*). Often one method is chosen, without comparing it to other methods, or even mentioning other options. LULC research in West Africa does not take patterns into account; only percentages and size of classes (see *Mengistu and Salami, 2007, Akinyemi, 2013* and *Obiefuna et al., 2013).* Changes in landscape patterns are important as they can give information on for example, ecosystem health (Riiters et al., 1997) and water quality (Hunsaker et al., 1992). This is recognized by some researchers, but not used in the research itself (see *Obiefuna et al., 2013*). Most of the research is focused on a single area. This makes comparison of patterns or LULC changes with other areas difficult, as the methods that were used are likely optimized for just that single area (see *Mengistu and Salami, 2007* and *Akinyemi, 2013*).

This leads to little of the research being published in internationally acclaimed journals, where it could raise awareness. The exception to this is research focused on disease control and to a lesser degree nature conservation research. It is clear that more resources are available for this type of research through international aid and/or subsidies. This leads to more sophisticated research with modern methods. This research is usually done by international researchers, often assisted by local authorities (see *Moiroux, et al. 2013, Whitehorn and Farrar, 2010, Hartfield et al., 2011, Clerici et al., 2006, Coetzer et al., 2013* and *Dowhaniuk et al., 2014).* No research that deals with coupling diseases (or disease risk) with changing landscape patterns could be found. Research that uses landscape patterns to predict human influence in an area was also not found.

OBIA has been described as a new paradigm or scientific revolution by Blaschke, et al. (2014). However, it is currently hardly used in Africa, let alone West Africa. Only 12 papers dealing with OBIA were found compared to 870 'regular' remote sensing papers for the years 2011-2014 in Scopus. In the same time period roughly 10% of the remote sensing papers worldwide used OBIA in some form (see 3.5). OBIA is well-suited for anthropogenic change detection, because anthropogenic objects (for example buildings and roads) are generally more homogeneous and have distinct boundaries. This in contrast to most natural objects (Chen et al., 2012). This would make OBIA a valuable method to use in the, due to human influence, rapidly changing landscape of West Africa.

The above shows that using OBIA to determine land cover- and landscape pattern changes, as well as using those landscape patterns to devise a method to determine human influence will be a valuable addition to the research that has already been done in West Africa.

4. Methods & Data

4.1. Image acquisition and description

Two transects in West Africa of 60km by 10km at two different moments (1986 and 2013) were classified into six classes, i, with i = 1: urban with vegetation, 2: urban without vegetation, 3:

dense vegetation, 4: light vegetation, 5: bare soil/road/grassy fields and 6: water. This was done by using object-based image analysis on Landsat images (table 3).

Table 3. Landsat images from the United States Geological Survey (USGS, glovis.usgs.gov).The path and row are part of the Worldwide Reference System and are used to identify each image.

	Path	Row	Time 1	Time 2
Transect 1	199	55	14-1-1986	26-12-2013
Transect 2	201	55	12-1-1986	24-12-2013

Transect 1 is located roughly 300km from the coast (figure 3) and contains the second largest city in Guinea: Nzérékoré, with a population of approximately 300,000. Nzérékoré is located in the middle of the transect and covers approximately 5km by 5km. The Diécké Forest Reserve is located in the southwest of the transect (figure 4).

Transect 2 is located roughly 150km from the coast (figure 3) and contains the third largest city of Sierra Leone: Kenema with a population of approximately 188,000. In the northwest of the transect a small part of the Kambui Hills Forest Reserve is found, next to Kenema itself that covers approximately 7.5km by 5km. In the south of the transect the Gola West Forest Reserve is found (figure 4).

The most striking difference between the two transects was that while both urban areas greatly increased in size from 1986 to 2013, transect 1 showed an increase in forested area, but transect 2 showed a large decrease in forested area (figure 5 and 18).

Figure 3. Approximate locations (red dots) of the transects in Sierra Leone and Guinea.

Figure 4. Location and orientation of the transects (in blue).

4.2. Image pre-processing

To prepare the images for further use, the digital numbers (DNs) were converted to radiance values. To this end a model was built in the Erdas Imagine model maker tool. In the model the DN's of every band were converted into top of atmosphere spectral radiance.

$$L_{\lambda} = M_L Q_{cal} + A_L \quad (1)$$

L_{λ} = Top of atmosphere spectral radiance (Watts/(m2 * srad * μm))

M_L = Band-specific multiplicative rescaling factor from the metadata

A_L = Band-specific additive rescaling factor from the metadata

Q_{cal} = Quantized and calibrated standard product pixel values (DN)

After this conversion the bands that both the Landsat 8 and Landsat TM have in common (table 4 and 5) were identified. Subsequently bands that they did not have in common were removed from the images.

Table 4. Landsat 8 bands used (2013 image). The resolution for all bands is 30m.

Band	**Wavelength (µm)**
Band 2 - Blue	0.45 - 0.51
Band 3 - Green	0.53 - 0.59
Band 4 - Red	0.64 - 0.67
Band 5 - Near Infrared (NIR)	0.85 - 0.88
Band 6 - SWIR 1	1.57 - 1.65
Band 7 - SWIR 2	2.11 - 2.29

Table 5. Landsat TM bands used (1986 images). The resolution for all bands is 30m.

Band	**Wavelength (µm)**
Band 1 - Blue	0.45-0.52
Band 2 - Green	0.52-0.60
Band 3 - Red	0.63-0.69
Band 4 - Near Infrared (NIR)	0.76-0.90
Band 5 - SWIR 1	1.55-1.75
Band 7 - SWIR 2	2.08-2.35

Table 6. Mean radiance (L_λ) values for the six bands that were used and the NDVI.

Transect	**Blue**	**Green**	**Red**	**NIR**	**SWIR-1**	**SWIR-2**	**NDVI**
1 - 1986	48.60	37.62	26.07	51.59	6.727	1.263	0.3285
1 - 2013	49.46	37.13	23.91	59.71	8.804	1.416	0.4282
2 - 1986	48.90	37.58	25.49	52.23	6.621	1.197	0.3441
2 - 2013	59.80	45.26	29.47	63.21	8.721	1.338	0.3640

4.3. Segmentation using Object Based Image Analysis

The object-based image analysis (OBIA) was done through use of eCognition. As the multi-resolution segmentation (MRS) approach is the most commonly used method in landscape ecology this was the method used for this research (see chapter 3.3).

The image was segmented by using the red, NIR and SWIR-1 bands. These bands were chosen because they showed the greatest differences between their average values and it led to slightly better results based on visual inspection. The following parameters were used: scale 2, shape 0 (see chapter 3.3.1).

This approach led to better delineated rivers and roads when compared to segmentation approaches found in literature. This conclusion was based on visually comparing the results of the approaches to the Landsat images and current (2014) images through Google Maps. The approaches found in literature were usually created for higher resolution satellite imagery where shape can be more easily distinguished. More on this can be found in the discussion (see 6.4).

4.4. Land cover classification

The ground truth in 1986 was based on the interpretation of the images by the author. For the images taken in 2013 the ground truth was a combination of the interpretation of the images by the author and Google Images. A step-by-step approach was used for the classification. First dense vegetation/no dense vegetation was classified, then urban no urban, and so on (table 7).

The following classes were chosen: Dense vegetation, light vegetation, water, urban with vegetation, urban without vegetation and bare soils, roads and grassy fields.

Dense vegetation and water were chosen because they were assumed to be the natural state of the landscape and therefore can be used to estimate the amount of human influence in the landscape. The light vegetation class was chosen as it contains agriculture, plantations and meadows where the largest difference in change between the two transects was seen. Urbanization is an important factor in landscape and mosquito habitat changes. It was decided to split urban into two classes: urban without vegetation representing densely populated areas and urban with vegetation representing more sparsely populated areas. Finally the bare soil, roads and grassy fields class was chosen to classify the areas without buildings and very little vegetation. This class was kept fairly broad as distinguishing between its various parts proved difficult due to the 30m resolution of Landsat.

4.4.1. Dense Vegetation

Dense vegetation was classified based on the Normalized Difference Vegetation Index (NDVI, equation 2):

$$NDVI = \frac{NIR-Red}{NIR+Red} \quad (2)$$

NIR = Mean value of the near infrared band of the image object
Red = Mean value of the red band of the image object

However, in all of study areas there were forest reserves present with a vegetation that was very different from the rest of the study areas. Based on Google Images and photographs taken in the area it was determined that these forest reserves had to be classified as dense vegetation. However, the forest reserves were difficult to classify as dense vegetation based on the NDVI. As the red band showed the largest difference between the forest reserve and the rest of the area it was decided to use this band instead as the basis for the classification of the forest reserves as dense vegetation. For transect 1 1986 and transect 2 1986 all image objects with a mean red value lower than 25.5 were classified as dense vegetation. For transect 1 2013 and transect 2 2013 these values were 22.5 and 27.5 respectively.

4.4.2. Urban

Image objects with a Red Ratio (equation 3) of over 0.24 and a brightness higher than 31.66 were classified as urban with vegetation. Brightness was defined as the total of the mean band values (radiance) divided by the number of bands, six in this case.

$$\textit{Red Ratio} = \frac{Red}{Red + Blue + Green} \qquad (3)$$

Red = Mean value of the red band of the image object
Blue = Mean value of the blue band of the image object
Green = Mean value of the green band of the image object

Image objects classified as urban with vegetation were then classified as “urban no vegetation” when they had an NDVI of less than 0.1.

4.4.3. Water

All image objects not classified as dense vegetation and with an IR Ratio (equation 4) of 0.06 or lower were classified as water.

$$\textit{IR Ratio} = \frac{IR}{IR+NIR+Red} \qquad (4)$$

IR = Mean value of the infrared band of the image object
NIR = Mean value of the near infrared band of the image object
Red = Mean value of the red band of the image object

4.4.4. Bare soil/roads/grassy fields

All image objects that were not yet classified as dense vegetation with an NDVI between 0.15 and 0.3 were classified as “bare soil/road/grassy field”. All image objects with an NDVI lower than 0.15 and a relative border to water of 0.1 and higher were classified as bare soil/road/grassy field to correctly classify sand banks in the river. This rule was repeated 10 times. Then all image objects that were classified as urban with a distance to water of 7 pixels or less were also classified as bare soil/road/grassy field. The last two rules were implemented to remove image objects in and around the river that were incorrectly classified as urban.

For transect 1 2013 the upper range of the NDVI was changed to 0.4.

4.4.5. Light and dense vegetation

All image objects except those already classified as dense vegetation were classified as light vegetation if their NDVI was over 0.3 (0.4 for transect 1 2013). Image objects that were unclassified or were classified as light vegetation were then classified as dense vegetation if they had an NDVI of over 0.4 for transect 1 1986, 0.5 for transect 1 2013 and 0.425 for transect 2. The reason for these different threshold values was because of the differences in overall NDVI in the different images (table 6). See the discussion for a possible explanation for this large increase in NDVI.

4.4.6. Unclassified image objects

Remaining image objects with a relative border to water of 0.5 or higher were classified as water. This was to remove image objects that were incorrectly classified as bare soil/road/grassy field instead of shallow water. Unclassified image objects were then placed in the bare soils/road/grassy field class when they had an NDVI lower than 0.2. The reason they were placed in this class was because the unclassified image objects were all on the border between urban and vegetation and usually a mix between these two classes.

4.5. Post-processing of images

After the images were fully classified the transects were divided in 6 equal parts of 10x10km. This was done to determine if different land cover compositions would have an effect on the changes, as well as making it possible to better identify human influence on landscape patterns. The transect was 10km wide and square parts was the simplest solution, hence the 10x10km parts.

Table 7. Step-by-step classification rules (top to bottom). No dense vegetation means all classes, including unclassified, except dense vegetation, px means pixels, rel. means relative. All criteria in a table-cell had to be fulfilled before a rule was executed.

New Class	**Old Class**	**Transect 1 1986**	**Transect 1 2013**	**Transect 2 1986**	**Transect 2 2013**
Dense vegetation	Unclassified	Mean red value < 25.5	Mean red value < 22.5	Mean red value < 25.5	Mean red value < 27.5
Urban with vegetation	Unclassified	Red Ratio > 0.24 Brightness > 31.66	Red Ratio > 0.24 Brightness > 31.66	Red Ratio > 0.24 Brightness > 31.66	Red Ratio > 0.24 Brightness > 31.66
Urban no vegetation	Urban with vegetation	NDVI < 0.1	NDVI < 0.1	NDVI < 0.1	NDVI < 0.1
Water	Unclassified	-	-	IR Ratio ≤ 0.06	IR Ratio ≤ 0.06
Bare soil, road, grassy field	No dense vegetation	0.15 < NDVI < 0.3	0.15 < NDVI < 0.4	0.15 < NDVI < 0.3	0.15 < NDVI < 0.3
Bare soil, road, grassy field	All	-	-	NDVI < 0.15 rel. border to water ≥ 0.1	NDVI < 0.15 rel. border to water ≥ 0.1
Bare soil, road, grassy field	Urban	Distance to water ≤ 7px	Distance to water ≤ 7px	Distance to water ≤ 7px	Distance to water ≤ 7px
Light vegetation	No dense vegetation	NDVI > 0.3	NDVI > 0.4	NDVI > 0.3	NDVI > 0.3
Dense vegetation	Light vegetation	NDVI > 0.4	NDVI > 0.5	NDVI > 0.425	NDVI > 0.425
Water	All	-	-	Rel. border to water > 0.5	Rel. border to water > 0.5
Bare soil, road, grassy field	Unclassified	NDVI < 0.2	NDVI < 0.2	NDVI < 0.2	NDVI < 0.2

4.6. Pattern analysis methods using Fragstats

Pattern analysis was used to characterize the changing landscape. This was done both spatially and temporally. The following landscape metrics were used, calculated with the Fragstats software (McGarigal et al., 2012). The following is based on McGarigal, 2014 unless otherwise noted:

The landscape metrics were chosen to have a mix of class and landscape metrics that combined will give information on both composition and configuration (see 2.2.2). This ensured that the characterization of the landscape was based on a wide range of information (table 8).

Table 8. Landscape metrics (after McGarigal, 2014)

Code	**Name**	**Type**	**Category**
PLAND	Percentage Land Cover	class	composition
NP	Number of Patches	class, landscape	composition
MSIEI	Modified Simpson's Evenness Index	landscape	composition
CONTAG	Contagion Index	landscape	configuration
PAFRAC	Perimeter Area Fractal Dimension	class, landscape	configuration

Percentage of landscape (PLAND)

PLAND equals the percentage the landscape comprised of the corresponding class. It equals the sum of the areas (m^2) of all patches, divided by the total landscape area (m^2), and multiplied by 100 (to convert to a percentage). This metric was used to calculate the land cover percentages per class in the area.

$$PLAND_i = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} (100) \qquad (5)$$

P_i = proportion of the landscape occupied by each class I (0-100%)

a_{ij} = area (m^2) of patch ij

A = total landscape area (m^2)

N = total number of patches belonging to class i

Number of patches (NP)

This metric equals the number of patches of the corresponding patch type (6) and the total number of patches in the entire landscape (7). This method was used to give a simple measure of the fragmentation of the landscape.

$$NP_i = n_i \text{ (class)} \qquad (6)$$

$$NP = N \qquad (7)$$

n_i = number of patches in the landscape of class i

N = Total number of patches in the landscape

Modified Simpson's Evenness Index (MSIEI)

MSIEI is a measure of evenness. An even distribution of area among patch types results in maximum evenness. This means it is the complement of dominance. This metric was used to describe the heterogeneity of the landscape.

$$MSIEI = \frac{-\ln \sum_{i=1}^{m} PLAND^2}{\ln m} \tag{8}$$

m = number of classes present in the landscape, excluding the landscape border if present.

Contagion

Contagion measures the extent to which classes are aggregated or clumped. High values are usually the result of a landscape with several large patches, while low values are the result of many small and dispersed patches. Contagion is widely used in landscape ecology because it seems to be an effective measure of clumpiness on categorical maps (such as land cover maps).

$$CONTAG = \left[1 + \frac{\sum_{i=1}^{m} \sum_{k=1}^{m} \left[PLAND \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right] \circ \left[\ln\left(PLAND \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right]}{2 \ln m}\right](100) \tag{9}$$

g_{ik} = number of adjacencies (joins) between objects of classes i and k based on the *double-count* method*
m = number of classes present in the landscape

*In the double-count method, each object adjacency is counted twice and the order of objects is preserved. For more on the subject please consult Riiters et al. (1996).

Perimeter-area fractal dimension (PAFRAC)

PAFRAC reflects shape complexity across a range of spatial scales (patch sizes). When large and small patches have simple geometric shapes the PAFRAC is low. The more complex the shapes, the higher the PAFRAC is. PAFRAC is calculated by dividing 2 by the slope of the regression line obtained by regressing the logarithm of the patch area (m^2) against the logarithm of the patch perimeter (m).

$$PAFRAC_i = \frac{2}{\frac{\left[n_i \sum_{j=1}^{n}\left(\ln p_{ij} \cdot \ln a_{ij}\right)\right] - \left[\left(\sum_{j=1}^{n} \ln p_{ij}\right)\left(\sum_{j=1}^{n} \ln a_{ij}\right)\right]}{\left(n_i \sum_{j=1}^{n} \ln p_{ij}{}^2\right) - \left(\sum_{j=1}^{n} \ln p_{ij}\right)^2}} \tag{10}$$

$$PAFRAC = \frac{2}{\frac{\left[N \sum_{i=1}^{m}\sum_{j=1}^{n}\left(\ln p_{ij} \cdot \ln a_{ij}\right)\right] - \left[\left(\sum_{i=1}^{m}\sum_{j=1}^{n} \ln p_{ij}\right)\left(\sum_{i=1}^{m}\sum_{j=1}^{n} \ln a_{ij}\right)\right]}{\left(N \sum_{i=1}^{m}\sum_{j=1}^{n} \ln p_{ij}{}^2\right) - \left(\sum_{i=1}^{m}\sum_{j=1}^{n} \ln p_{ij}\right)^2}} \tag{11}$$

a_{ij} = area (m^2) of patch ij

p_{ij} = perimeter (m) of patch ij

n_i = number of patches in the landscape of class i

m = number of classes present in the landscape

N = total number of patches in the landscape.

PAFRAC is calculated using regression analysis and because of this a small sample size can lead to invalid results. According to McGarigal (2014) the results are probably only useful with a sample size of over 20. Therefore it was decided to only use PAFRAC in the analysis if the total number of patches per class in a section was higher than 20. In the appendix all PAFRAC values will be listed for the sake of completeness.

5. Results

The classification and analysis of transect 1 and 2 were separated from each other to offer a clearer view of each transect.

5.1. Classification and analysis of Transect 1

In this section the results of the classification and the landscape patterns analysis of transect 1 are listed. As the amount of water in transect 1 was extremely small this class was not taken into account. For completeness sake the statistics of the water class are listed in the appendix.

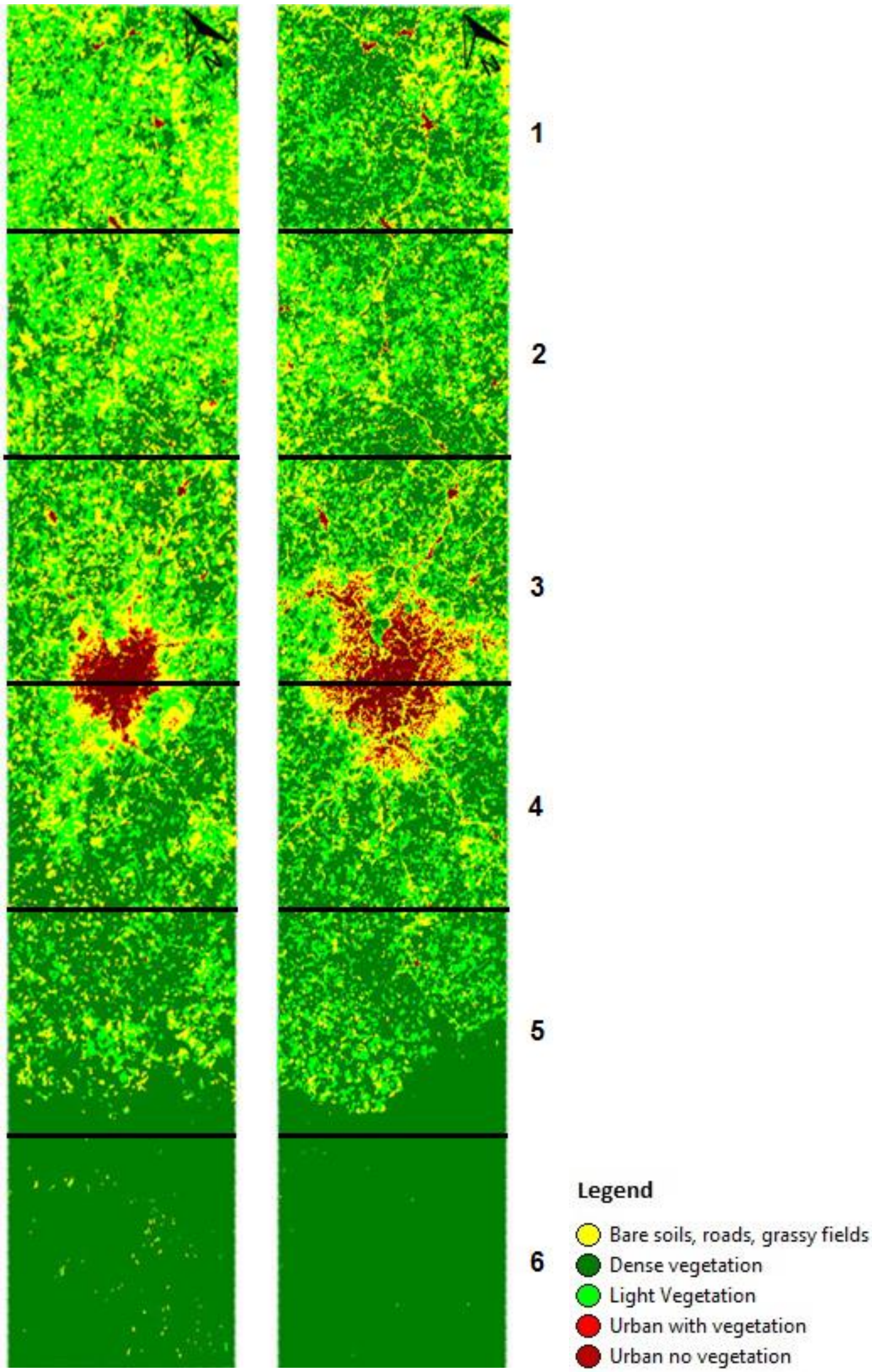

Figure 5. Classified image of transect 1 (10x60km) with the section number to the right. Left: 1986. Right: 2013.

As noted in section 4.4 the transect was divided in six sections of 10x10km. The sections were numbered from top to bottom (north to south).

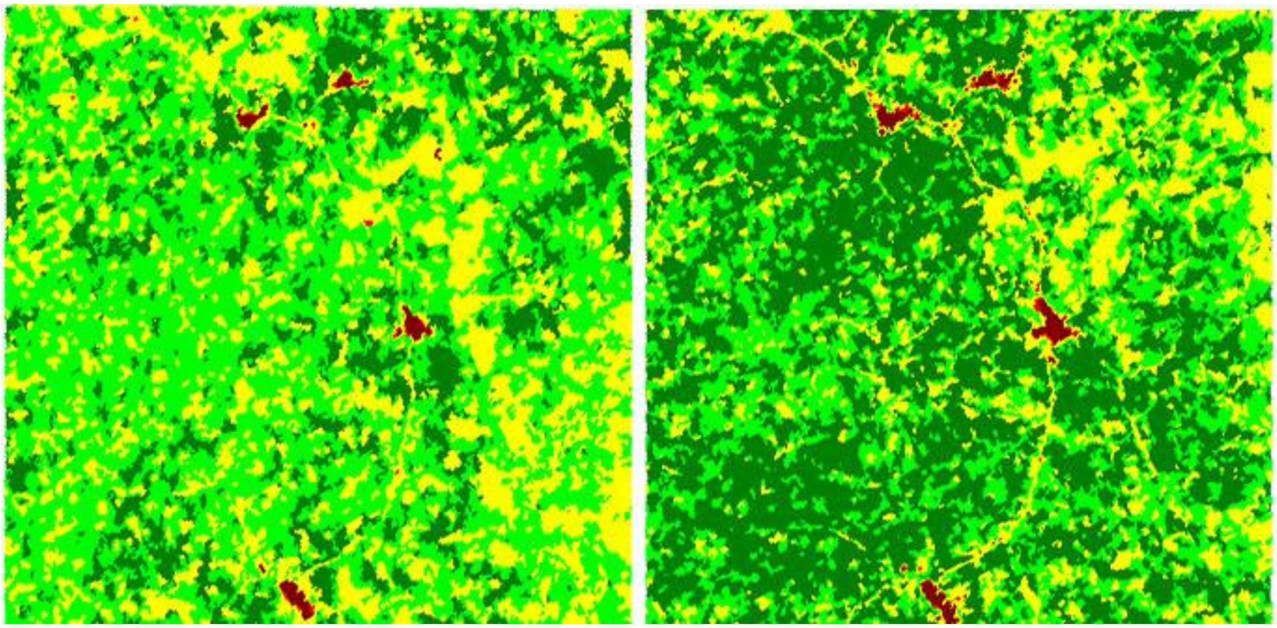

Figure 6. Classified image of transect 1 section 1. Left: 1986. Right: 2013 (legend figure 5).

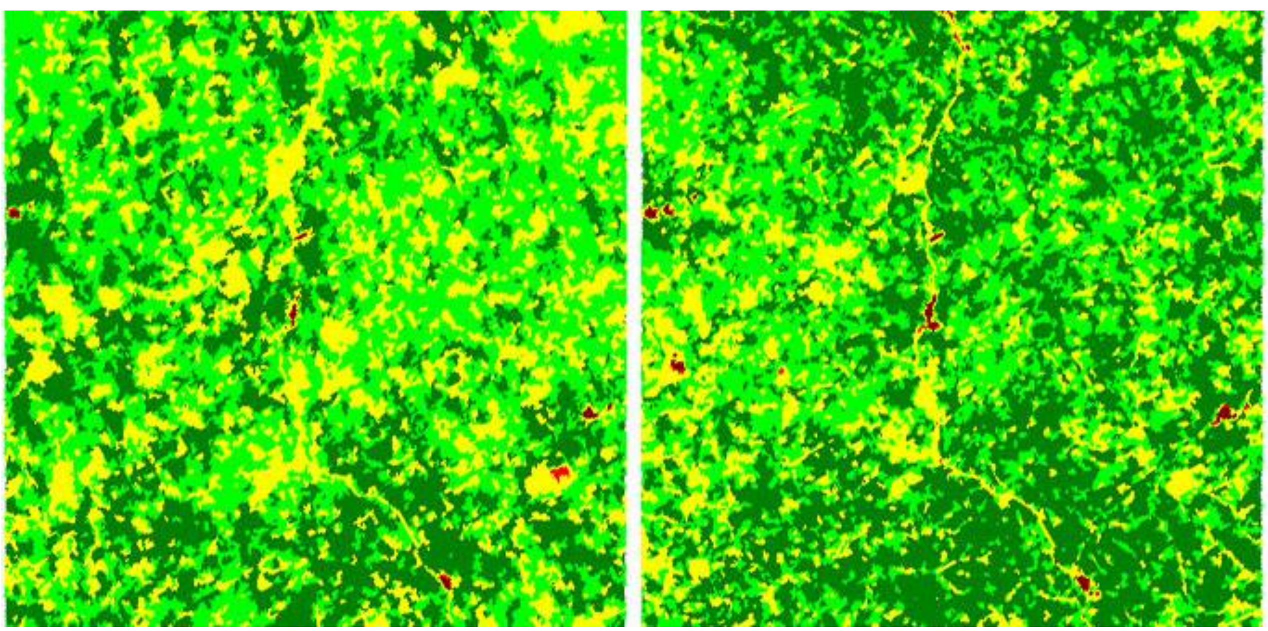

Figure 7. Classified image of transect 1 section 2. Left: 1986. Right: 2013 (legend figure 5).

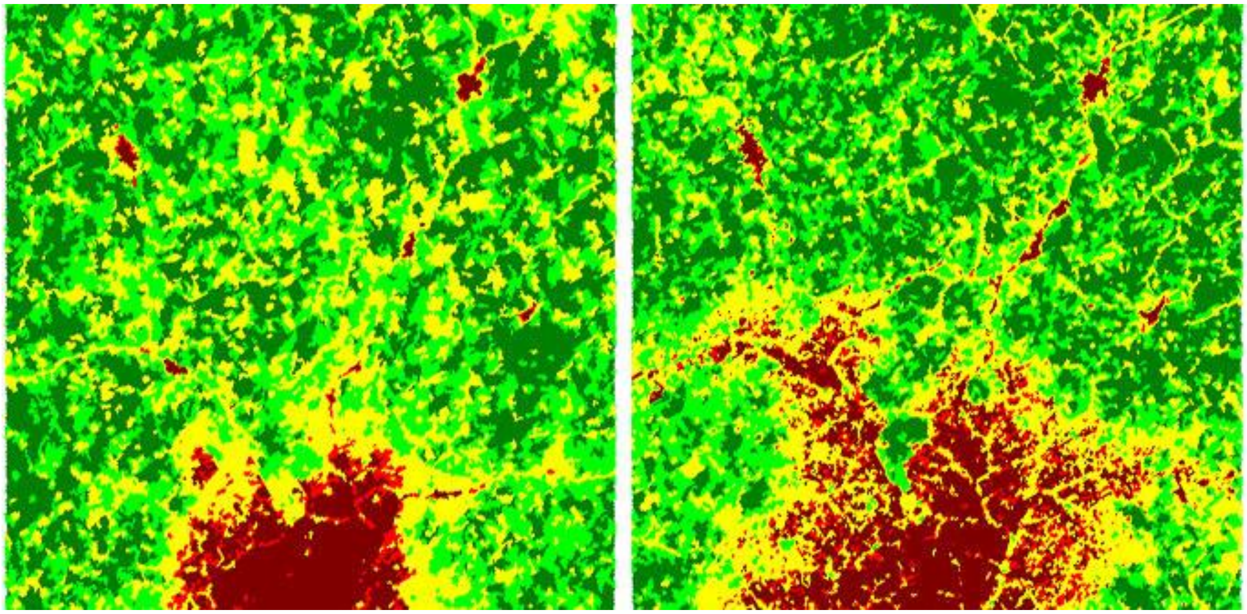

Figure 8. Classified image of transect 1 section 3. Left: 1986. Right: 2013 (legend figure 5).

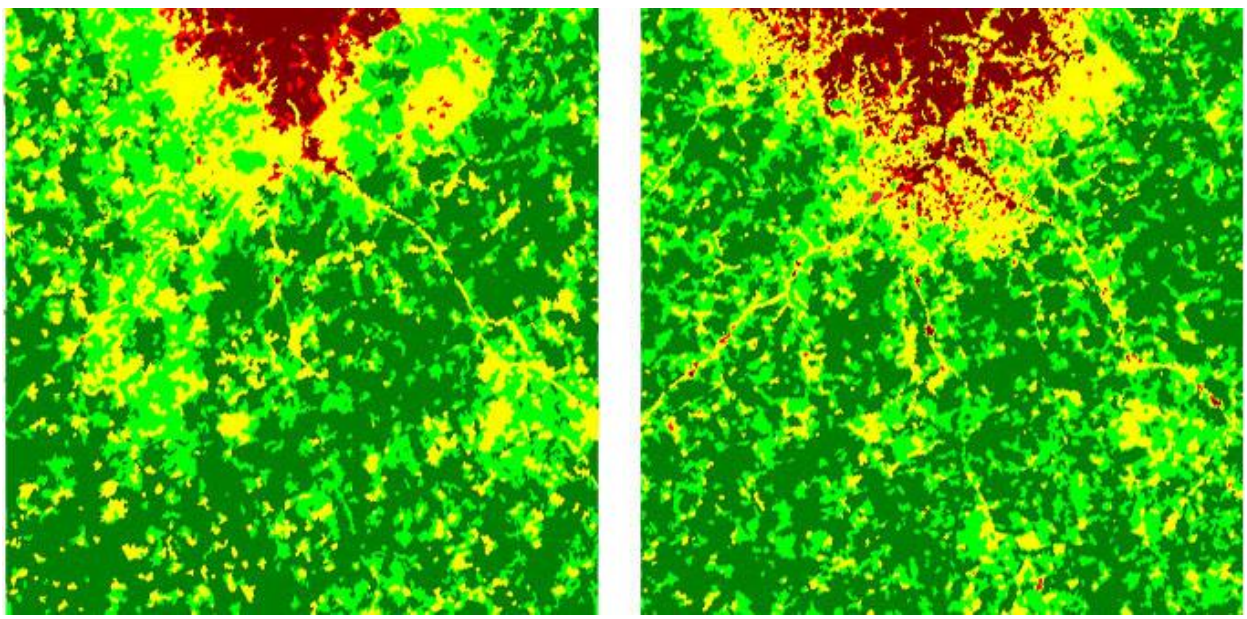

Figure 9. Classified image of transect 1 section 4. Left: 1986. Right: 2013 (legend figure 5).

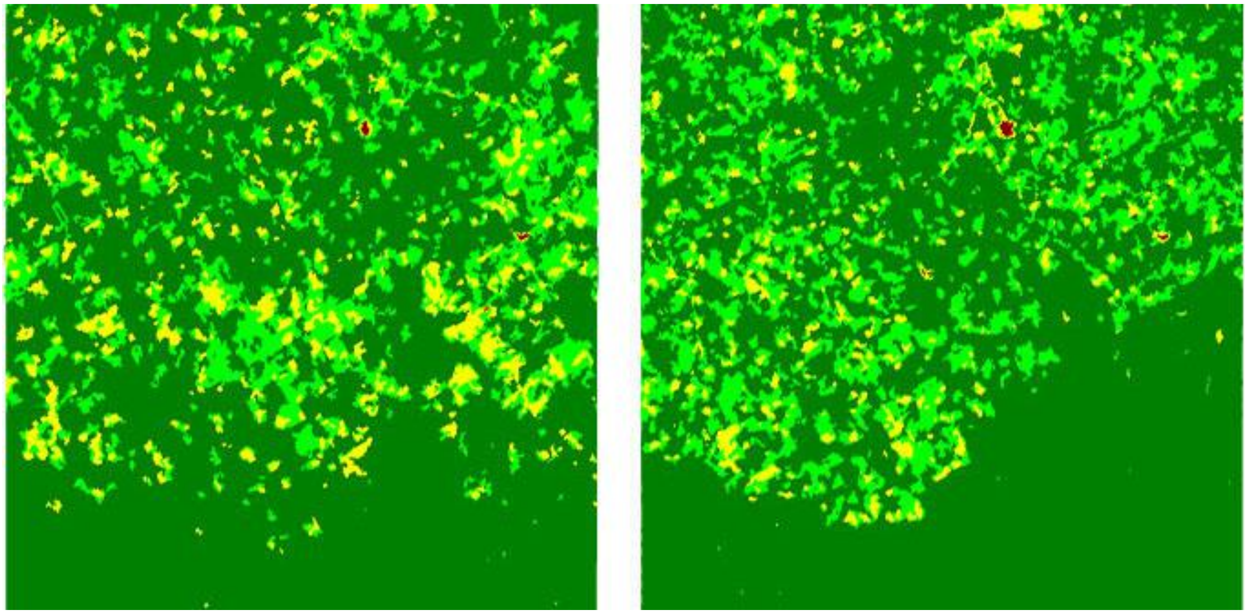

Figure 10. Classified image of transect 1 section 5. Left: 1986. Right: 2013 (legend figure 5).

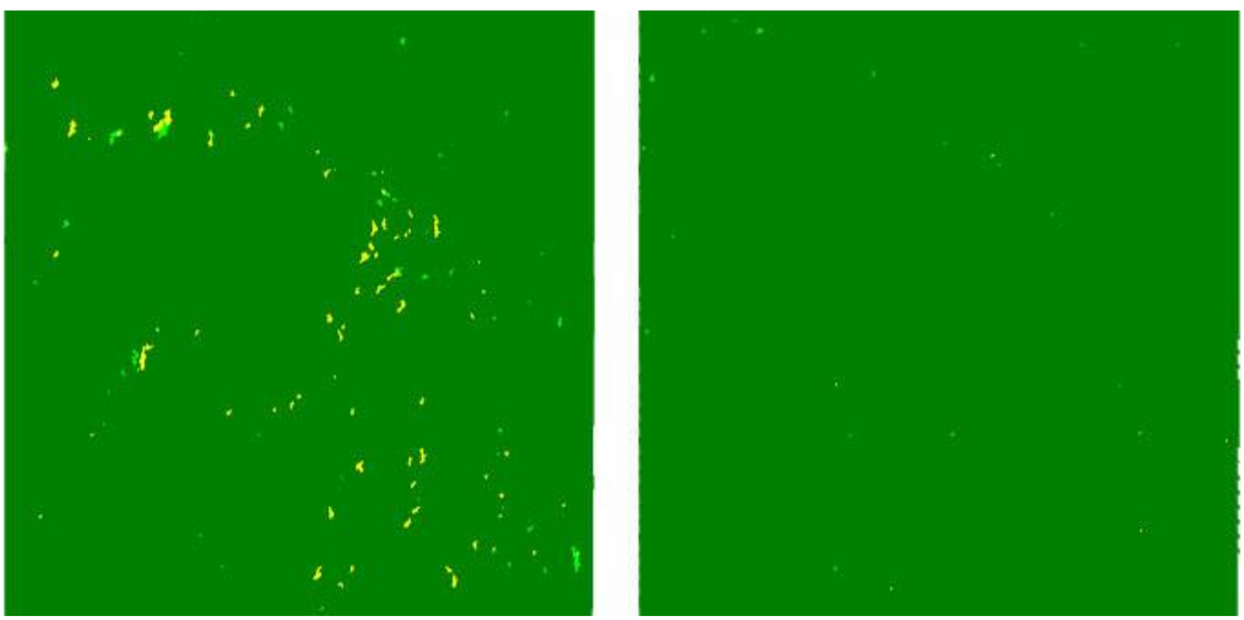

Figure 11. Classified image of transect 1 section 6. Left: 1986. Right: 2013 (legend figure 5).

5.1.1. Patch metrics transect 1

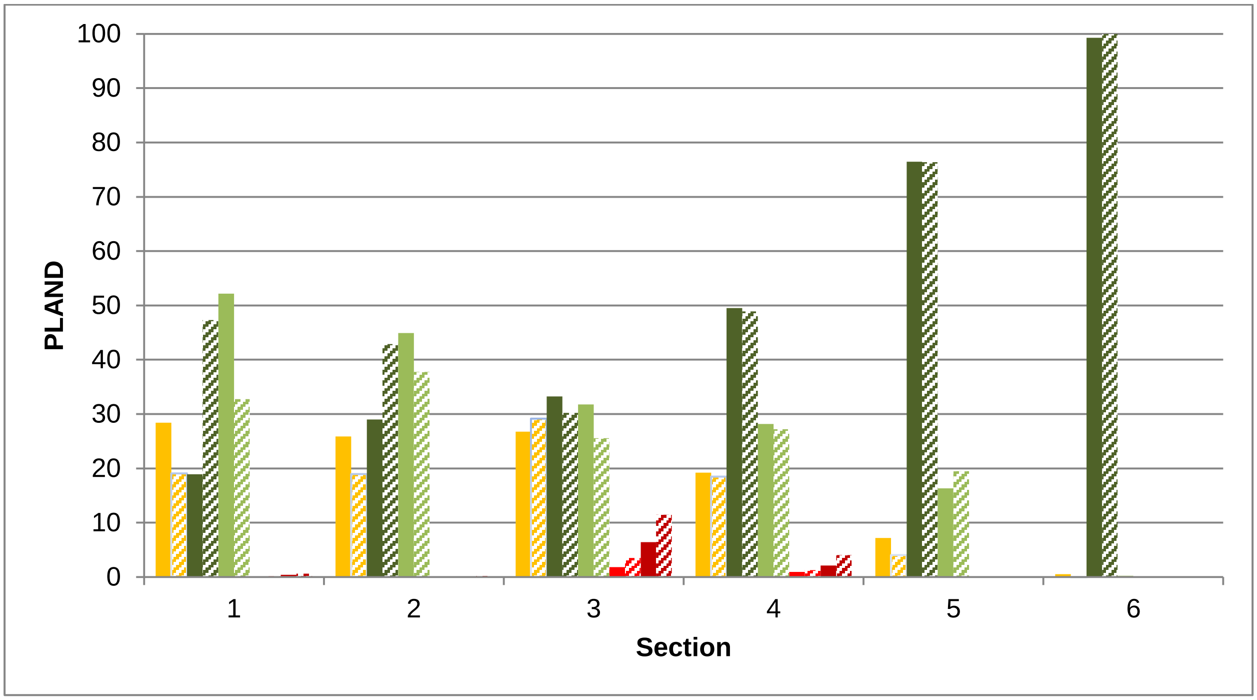

Figure 12. Percentage land cover (PLAND) - transect 1 – 1986 (solid) and 2013 (patterned) (legend figure 5).

A clear change was seen from 1986 to 2013. In 1986 the dense vegetation class kept increasing from north to south in the transect (figure 5). However, this was no longer the case in 2013 (figure 5). In 2013 the dense vegetation class increased with distance to the main urban area. In section 6 the dense vegetation class covered nearly 100% of the section in both time periods. In sections 1 and 2 the dense vegetation class had greatly increased in percentage over time at the expense of light vegetation and bare soil, road, grassy field (figures 6 and 7).

The main urban area was located in sections 3 and 4 and almost doubled in size (figures 8 and 9). At the same time only small overall changes were seen in the other classes. However, a large redistribution of the classes was seen. In 2013 the bare soil, road, grassy field class was more concentrated around the main urban area at the expense of dense and light vegetation. Away from the main urban area the opposite was the case. In 1986 there was also a concentration of the bare soil, road, grassy field class around the main urban area, but it was not nearly as pronounced as it is in 2013.

In section 5 (figure 10) light vegetation increased at the expense of bare soil, road, grassy field. This section was also where the forest reserve started, marked by a sharp transition to dense vegetation. Section 6 (figure 11) was located fully within the forest reserve and was almost completely covered by dense vegetation. The small amount of light vegetation and bare soil, road and grassy field seen in 1986 had almost completely vanished in 2013.

In all sections the increase in the urban classes was largely seen around the location of urban areas present in 1986. Most of the smaller urban areas were concentrated along roads. An example of this could be seen in section 3 (figure 8).

Overall the amount of dense vegetation and urban area increased from 1986 to 2013, while light vegetation and bare soil, road, grassy field decreased.

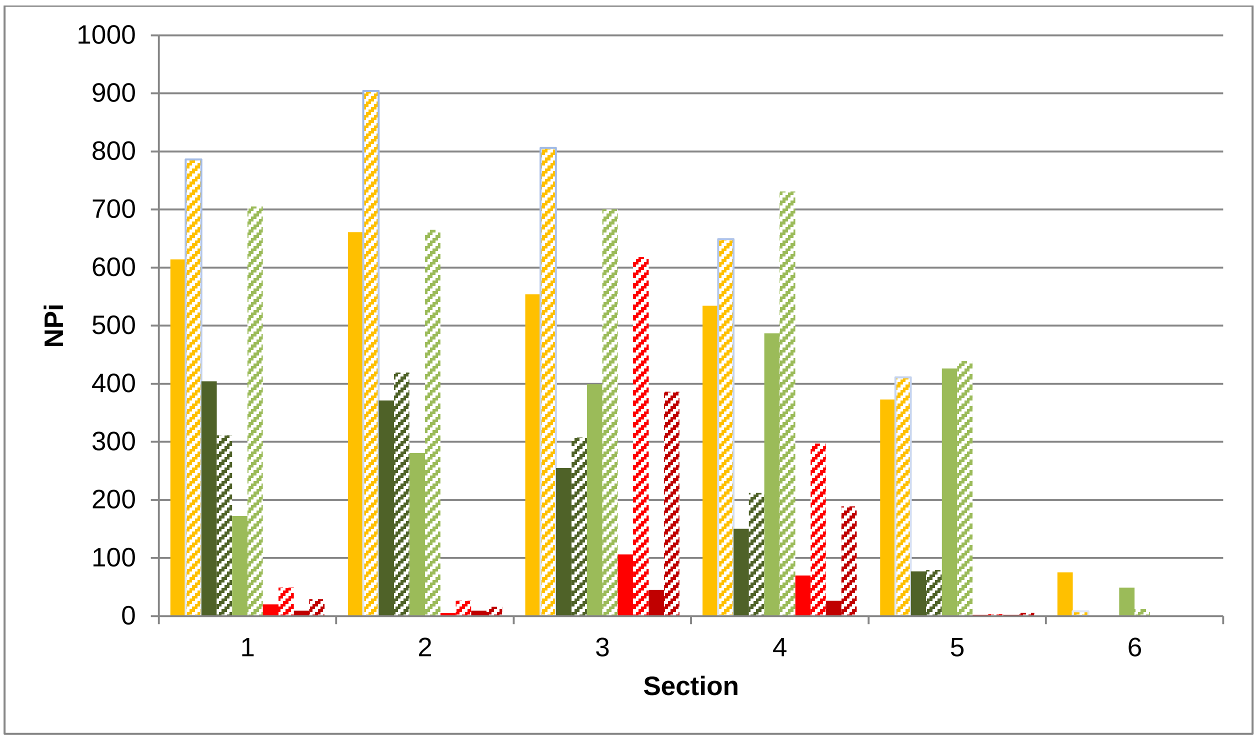

Figure 13. Number of patches (NPi) - transect 1 – 1986 (solid) and 2013 (patterned) (legend figure 5).

The number of light vegetation patches in 1986 kept increasing from section 1 to 4 before decreasing from section 4 to 6. However, in 2013 the number of light vegetation patches was relatively stable around 700 between section 1 and 4, before quickly decreasing to almost zero in section 6.

The number of urban patches in sections 3 and 4 showed a large increase between 1986 and 2013. As can be seen in figures 8 and 9 the urban area looks more fragmented, with gulley- and channel-like features dividing the urban areas.

In general the number of patches showed a large increase from 1986 to 2013. All classes except dense vegetation showed this increase. This increase was concentrated in sections 1 to 4. Section 5 showed virtually the same results. In section 6 a large decrease in NP could be seen.

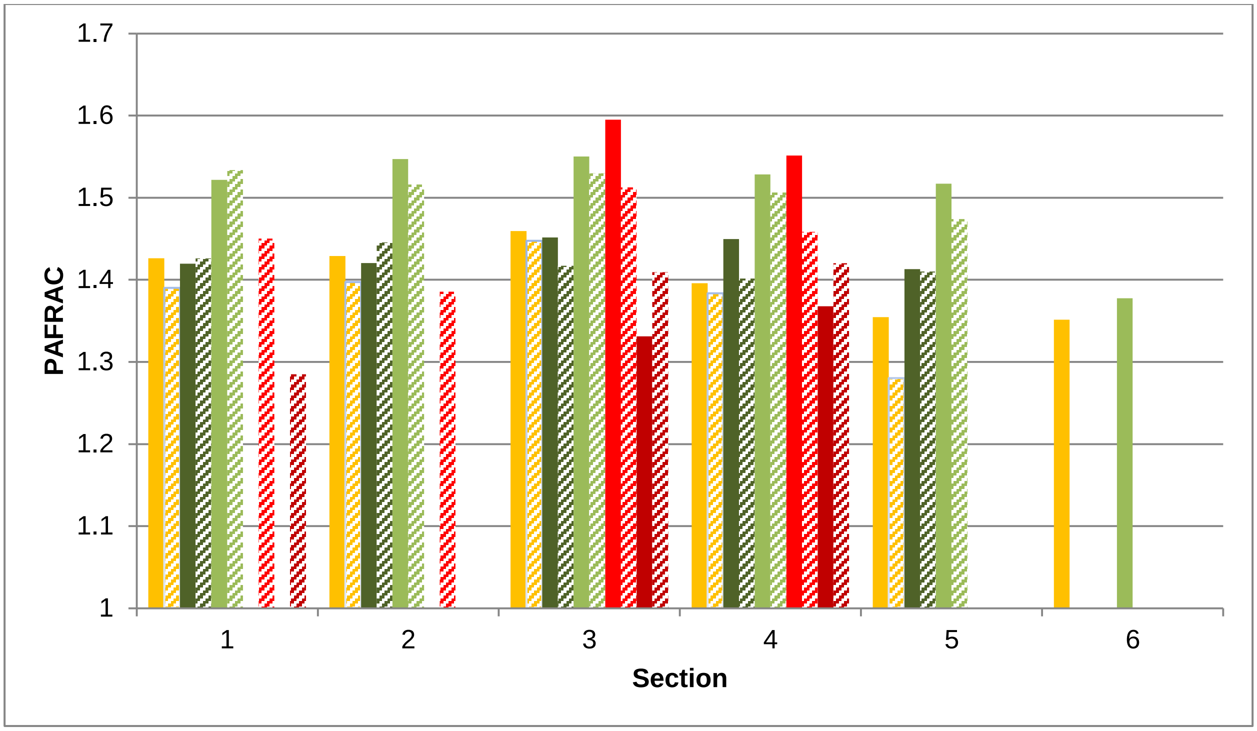

Figure 14. Perimeter Area Fractal Dimension (PAFRAC) - transect 1 – 1986 (solid) and 2013 (patterned) (legend figure 5).

PAFRAC was not calculated for every class in every section as it requires a sample size of >20 patches per section for meaningful results. The effect was that the urban classes could only be compared for section 3 and 4 because the main urban area was located there. Section 6 had very few patches (20) because it was almost entirely covered by dense vegetation in 2013 (figure 11). The total number of patches was far too low to calculate PAFRAC and thus it could not be compared to 1986.

Overall the PAFRAC in 2013 was lower than in 1986 for all classes. The exception was the urban without vegetation class, which had a higher PAFRAC for both sections in which it could be compared.

There were several changes over time in the results. The first was that the PAFRAC of the urban with vegetation and the urban without vegetation classes were more similar in 2013 than in 1986. The second was that the PAFRAC of the bare soil, road, grassy field class showed a far steeper decline from section 3 to 5 in 2013 when compared to 1986.

5.1.2. Landscape metrics transect 1

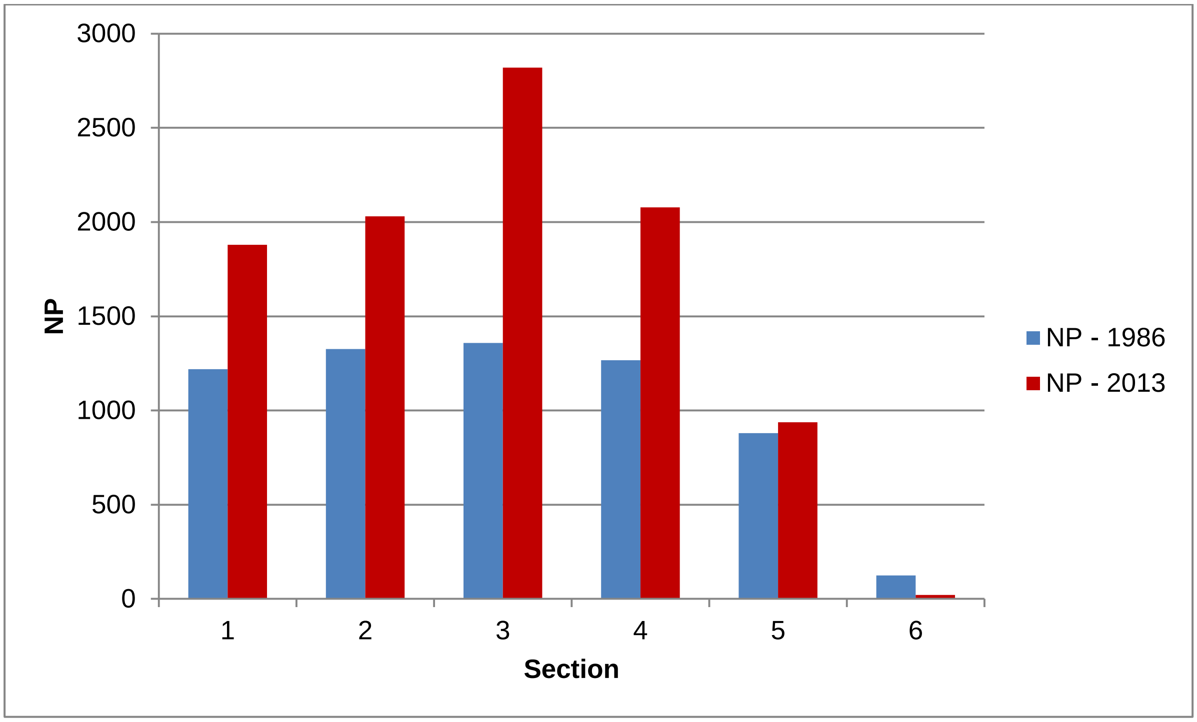

Figure 15. Number of patches (NP) - transect 1 – 1986 and 2013.

There were a higher number of patches in sections 1 to 4 in 2013 compared to 1986. This points to a more fragmented landscape. The largest increases were seen in sections 3 and 4 where the main urban area was located. The reason that these sections showed the largest increase was because the main urban area was far more fragmented in 2013 than in 1986 (figure 8 and 9). One would expect this to be the other way around, as an increase in population usually not only increases the area of a city, but also its density. More on this can be found in the discussion.

However, in section 5 the NP remained roughly unchanged: 880 in 1986 and 937 in 2013. In section 6 the NP in 2013 was actually a lot lower: 125 in 1986 and 21 in 2013. A possible explanation is that section 5 was partly located in a forest reserve and section 6 was fully located in a forest reserve. This forest reserve has seen an increase in dense vegetation, this led to a reduced number of patches and a less fragmented landscape in section 5 and 6.

All sections without forest reserve showed a large increase in NP. Almost all human activity in the forest reserves was (and is) prohibited and in the sections that contain these reserves only a slight increase (section 5) and a large decrease (section 6) in NP was seen. This is an indication that the fragmentation of the landscape is due to human influence.

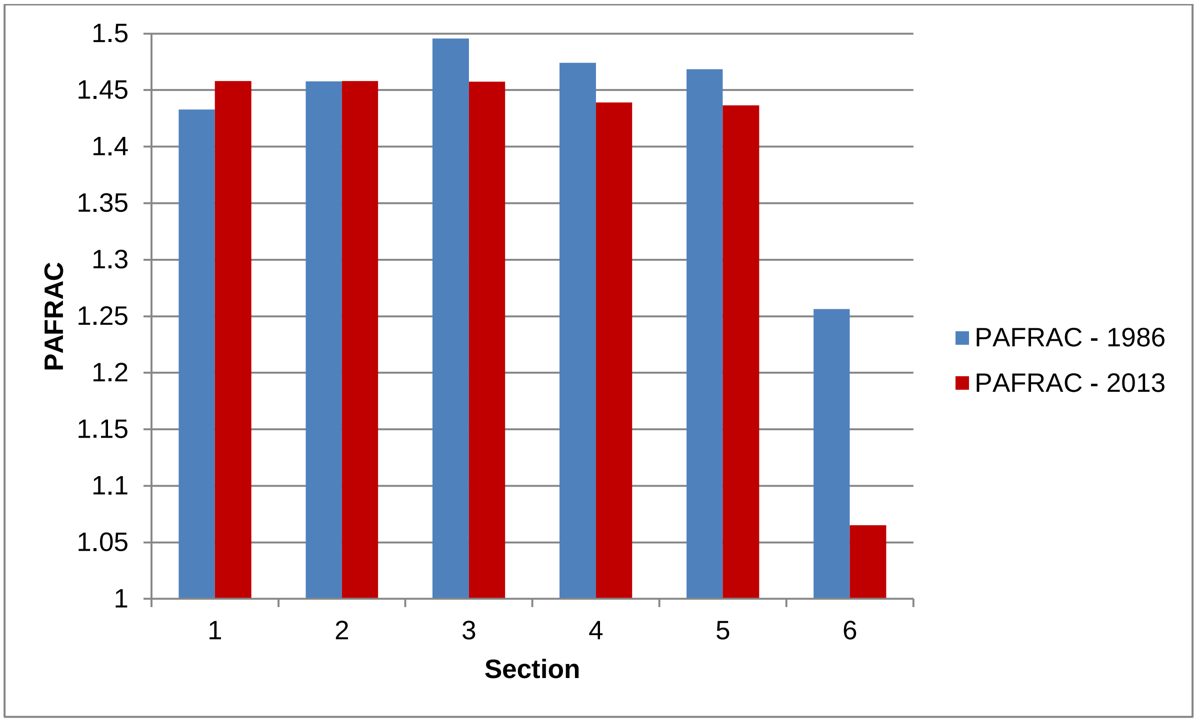

Figure 16. Perimeter Area Fractal Dimension (PAFRAC) - transect 1 – 1986 and 2013.

In section 1 the PAFRAC was slightly higher in 2013 than in 1986. While in section 2 the numbers were identical (1.4581). However, from section 3 to 6 the 2013 values were slightly lower than in 1986. The lower values in section 3 and 4 can be explained by the increase in urban area in those sections. In general the greater the human influence in an area, the lower the fractal dimension is, because humans simplify the landscape (O'Neill et al., 1997). However, there were no large changes in urban area in sections 1 and 5 (graph 1). In section 5 the increase can be explained by the large increase in the NP. In general smaller patches have a higher complexity. This would lead to an increase in PAFRAC. In section 5 the small decrease in PAFRAC despite the small increase in NP points to less complex patch shapes. It is likely that this is due to human influence. However, the changes in both metrics were fairly small and therefore it is possible that these changes were simply due to natural variation in the landscape over time. In section 6 there was a large decrease in the PAFRAC value, this was caused by the large increase in dense vegetation. A single patch of dense vegetation covered 99.97% of the section (see figure 9 and appendix). A patch of this size will have a relatively simple shape and will lead to a very low PAFRAC.

Overall the PAFRAC for 2013 was lower than in 1986. This points to a simplified landscape and an increase in human influence. Especially because sections 1 to 5 showed a (large) increase in NP and in general this should lead to a higher PAFRAC, rather than a lower one.

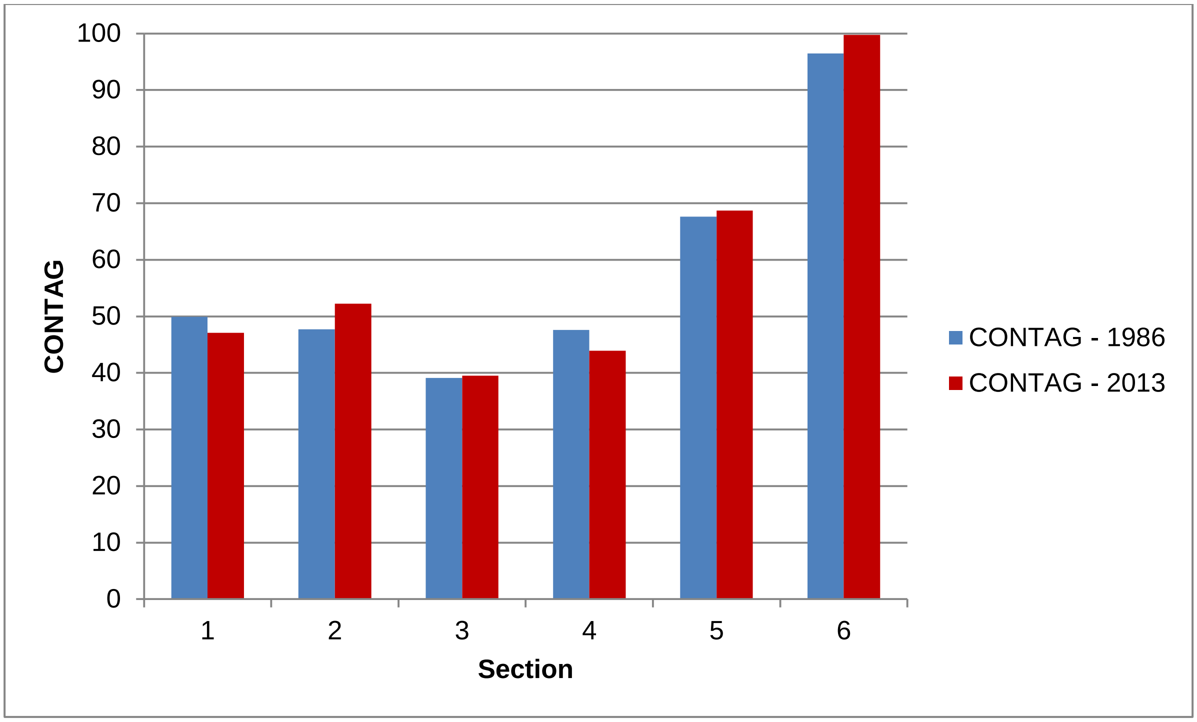

Figure 17. Contagion Index (CONTAG) - transect 1 – 1986 and 2013.

As seen above the CONTAG values were fairly similar for both time periods. Both hovered between 52 and 40 in sections 1 to 4. From section 4 to 6 the CONTAG sharply increased to nearly 100. The latter was the case because the forest reserve started in the southern part of section 5 and fully enclosed section 6 (figures 10 and 11). This led to large contiguous patches where the majority of the pixels are internal and all adjacent pixels were in the same class. The largest changes were seen in section 2 and 4. In section 2 the CONTAG was higher in 2013 than in 1986. This increase was attributed to an increase in dense vegetation that led to an increase in large contiguous patches (figure 7), despite the large increase in total number of patches in this section (graph 4). In section 4 the CONTAG in 2013 was lower than in 1986. Here the area of all the classes remained almost the same, with the exception of the urban classes that nearly doubled in area in this time period. However, this increase in urban area was not enough to offset the large increase in number of patches that led to less clumping. Particularly because the urban area in section 4 was more fragmented in 2013 than in 1986 (figure 9).

5.2. Classification and analysis of Transect 2

In this section the results of the classification and the landscape patterns analysis of transect 2 are listed.

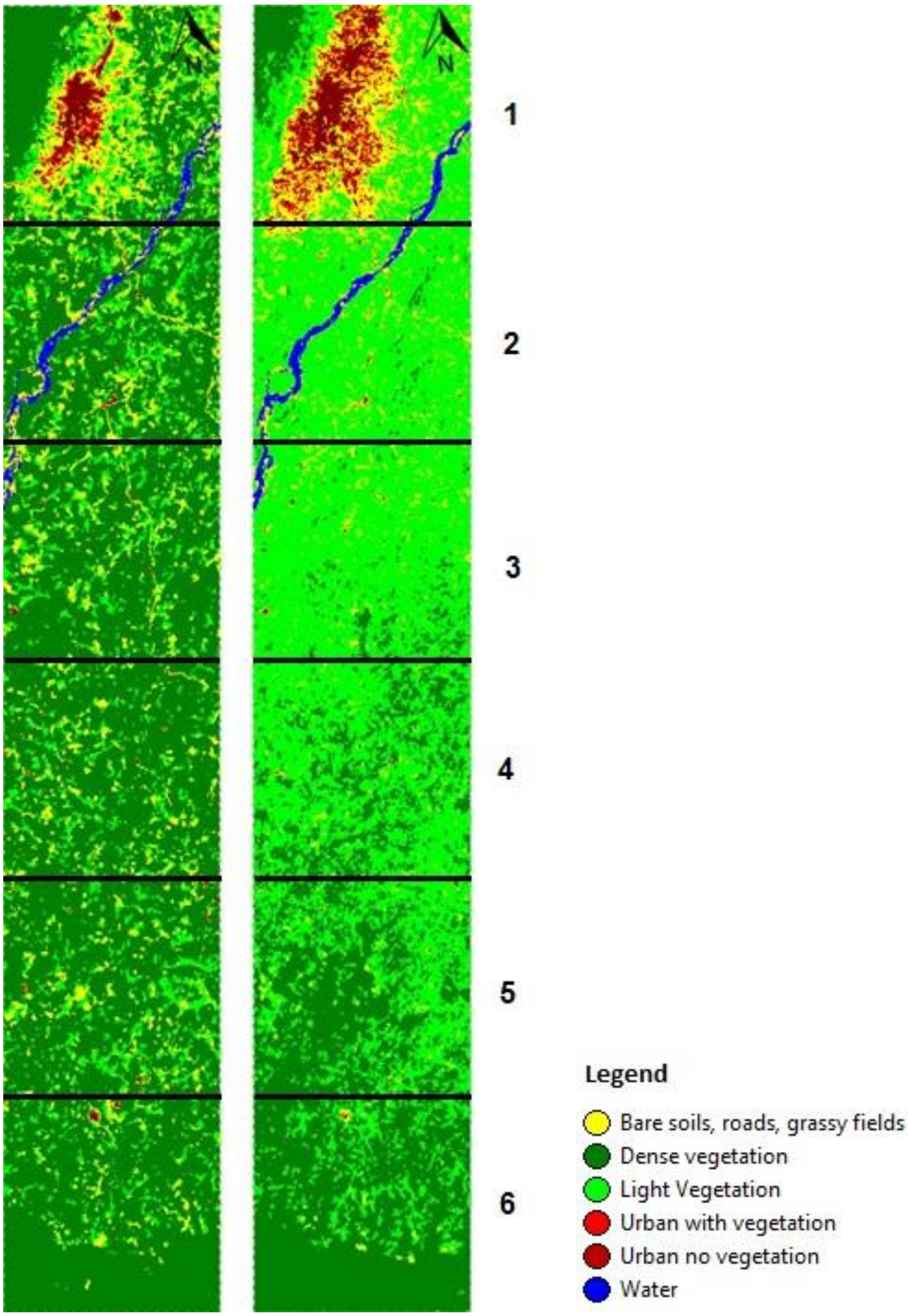

Figure 18. Classified image of transect 2 (10x60km) with the section number to the right. Left: 1986. Right: 2013.

As noted in section 4.4 the transect was divided in six sections of 10x10km. The sections were numbered from top to bottom (north to south).

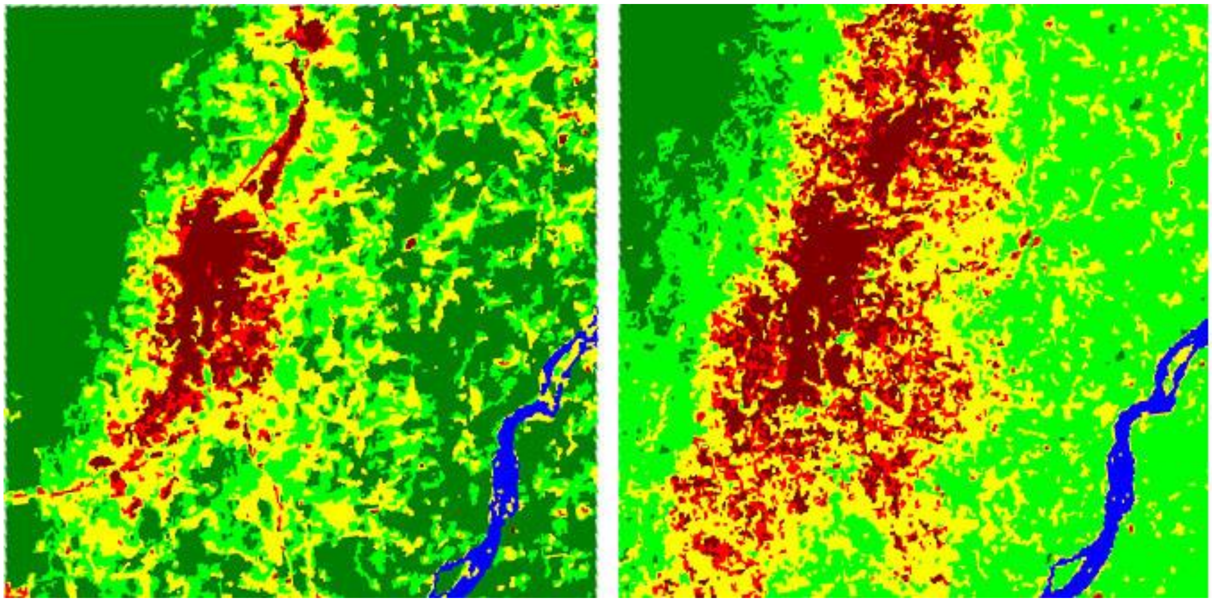

Figure 19. Classified image of transect 2 section 1. Left: 1986. Right: 2013 (legend figure 18).

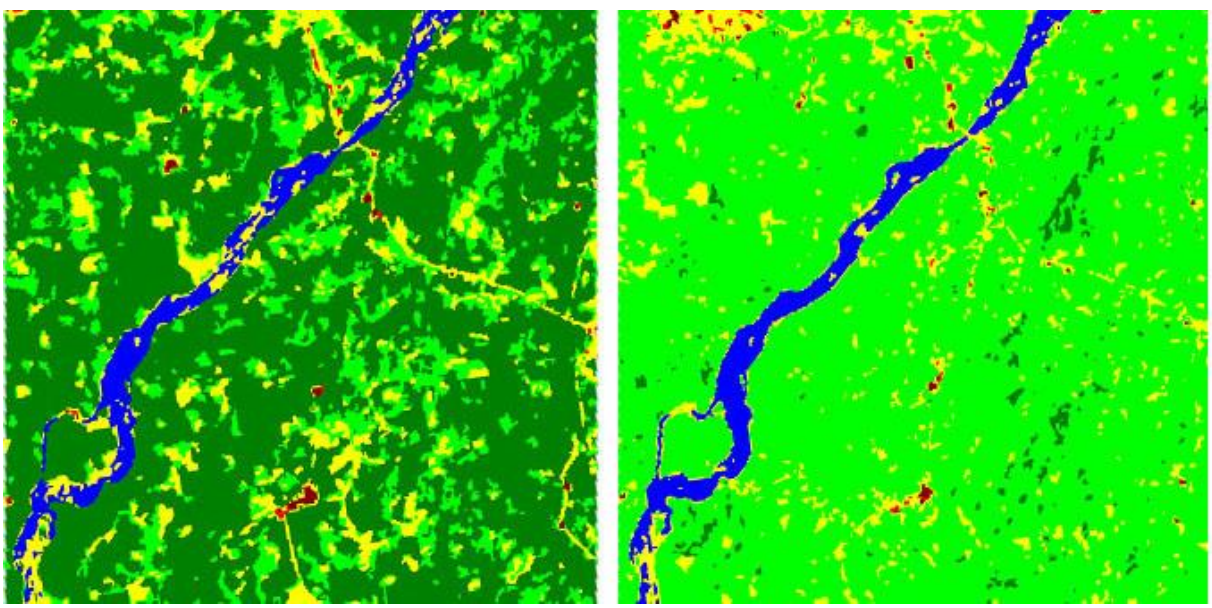

Figure 20. Classified image of transect 2 section 2. Left: 1986. Right: 2013 (legend figure 18).

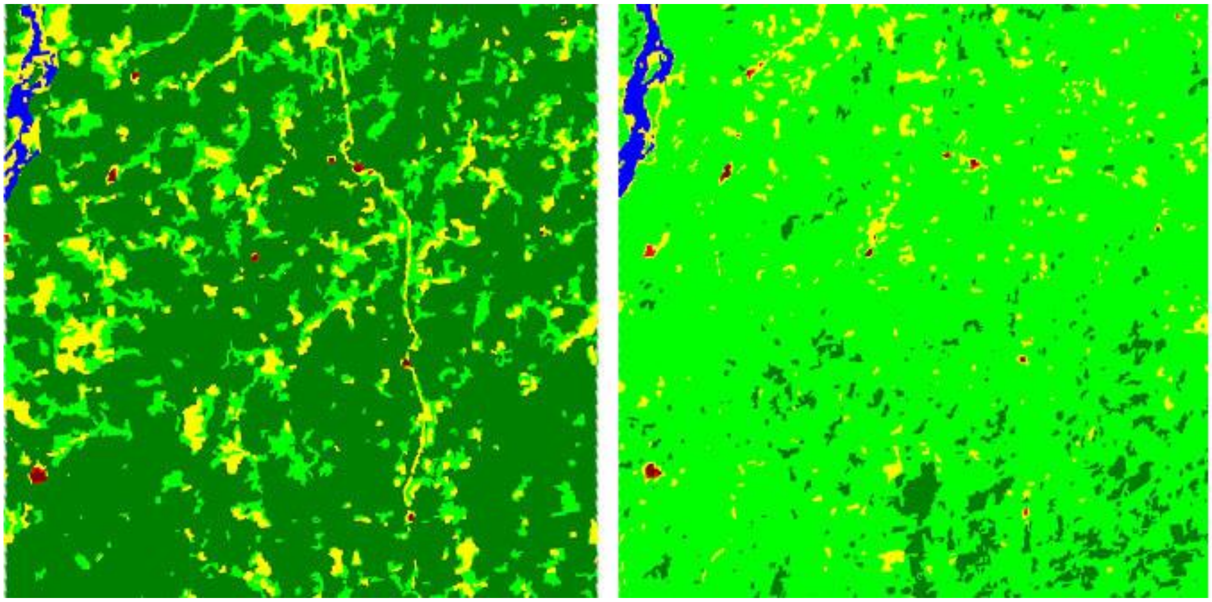

Figure 21. Classified image of transect 2 section 3. Left: 1986. Right: 2013 (legend figure 18).

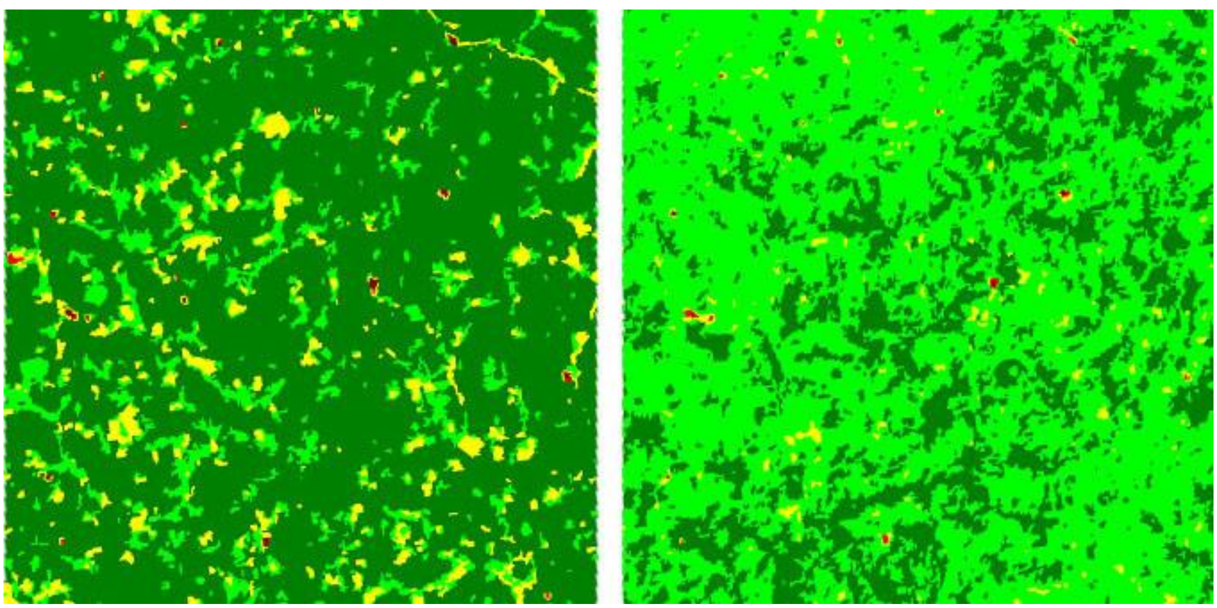

Figure 22. Classified image of transect 2 section 4. Left: 1986. Right: 2013 (legend figure 18).

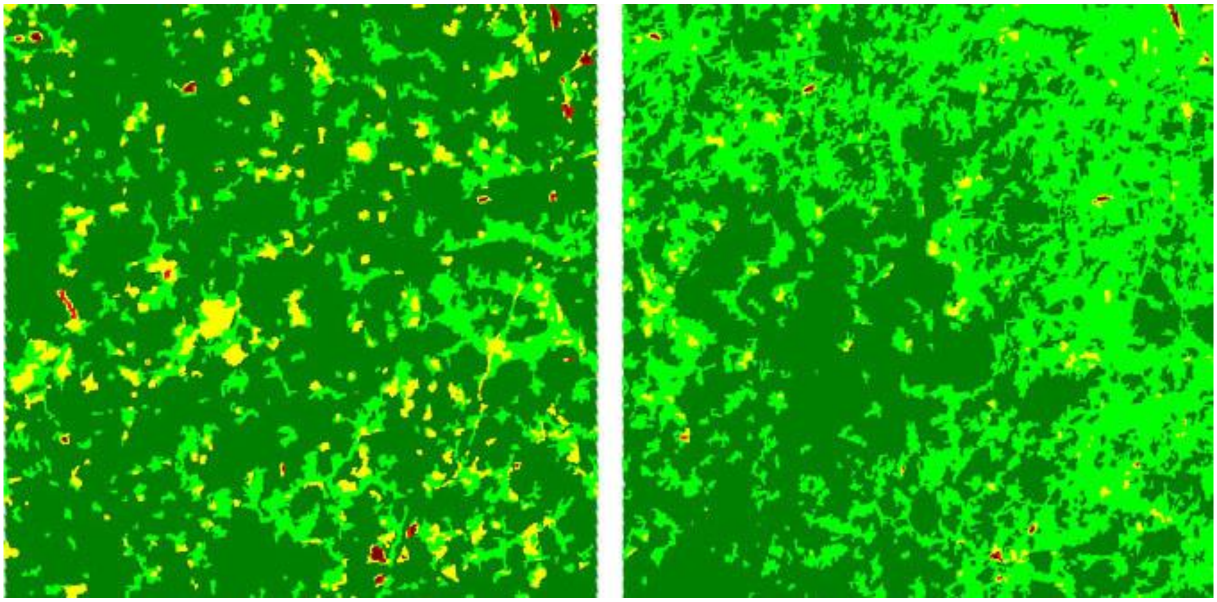

Figure 23. Classified image of transect 2 section 5. Left: 1986. Right: 2013 (legend figure 18).

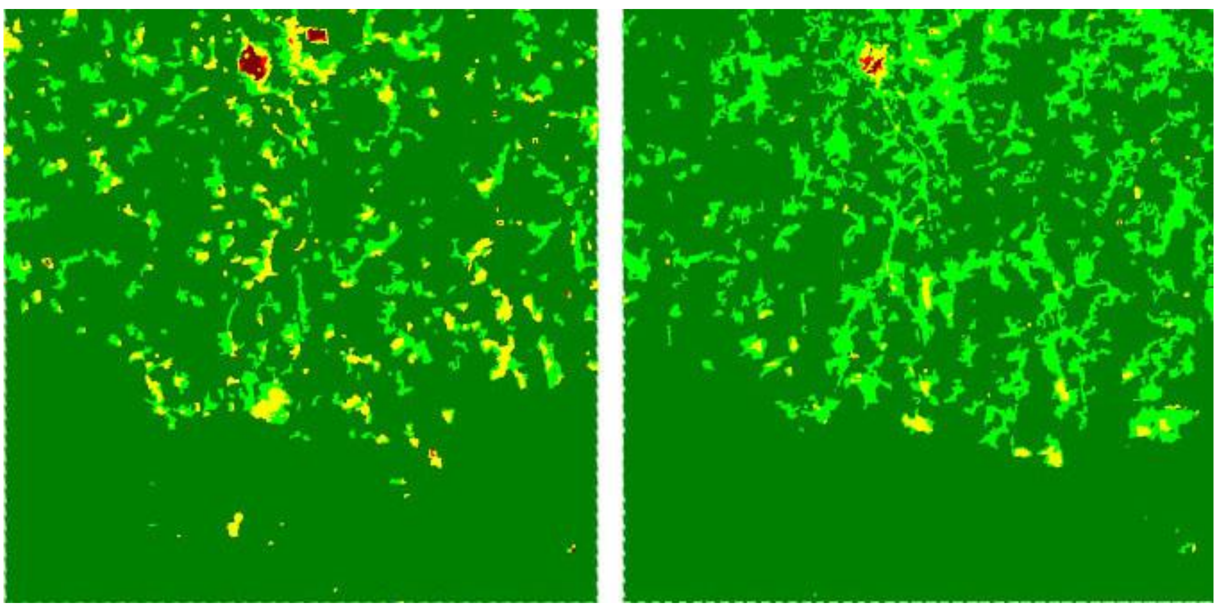

Figure 24. Classified image of transect 2 section 6. Left: 1986. Right: 2013 (legend figure 18).

5.2.1. Patch metrics transect 2

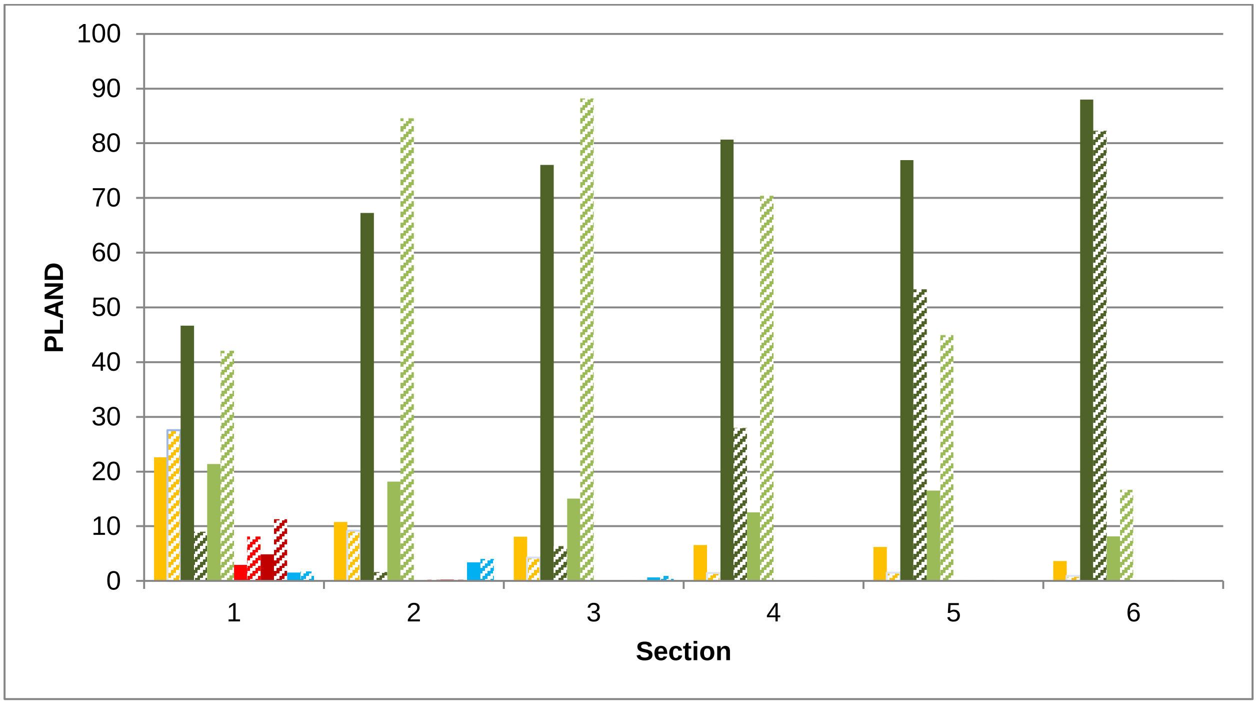

Figure 25. Percentage land cover (PLAND) - transect 2 – 1986 (solid) and 2013 (patterned) (legend figure 18).

A massive change was seen in the land cover in this transect. Dense vegetation dominated the area in 1986 (figures 20 to 24), but in 2013 it only dominated section 5 and 6 (figures 23 and 24). In sections 1 to 3 it virtually disappeared with the exception of the forest reserve in the northwest of section 1. Light vegetation became the dominant land cover in sections 1 to 4 in 2013. Dense and light vegetation both cover nearly half of the land in section 5 (53.34% and 44.99% respectively). Dense vegetation still dominated section 6 with a land cover of over 82%. This was because a forest reserve was located in the bottom part of this section. Overall the change from dense vegetation to light vegetation became less pronounced with increasing distance to the main urban area (figure 18).

The bare soil, road, grassy field class decreased by almost 50% in section 3 and disappeared almost entirely in sections 4 to 6. However, it remained stable in section 2 and increased again in section 1. The latter was caused by the main urban area that was located in section 1 (figure 19) and it saw a large increase in size between 1986 and 2013. As seen in transect 1 an increase in urban area was accompanied by a concentration of the bare soil, road, grassy field class around this urban area (figure 8 and 9).

While hard to see in figure 25 the urban areas in section 4, 5 and 6 greatly decreased in size. Some of the urban areas in 1986 were no longer visible in 2013 (figures 22, 23 and 24). However, the main urban area in section 1 (figure 19) greatly increased in size in the same period. It is possible that this is the result of people moving to the city from rural areas. Almost all urban areas in transect 1, including those far away from the main urban area, increased in size in the same period so this points to a very different development trajectory of the transects.

The PLAND of the water class remained virtually the same (figure 25). The small increase that was seen in section 2 was because the number of bare soil, road, grassy field patches (sandbanks and dunes) in the river declined (figure 20).

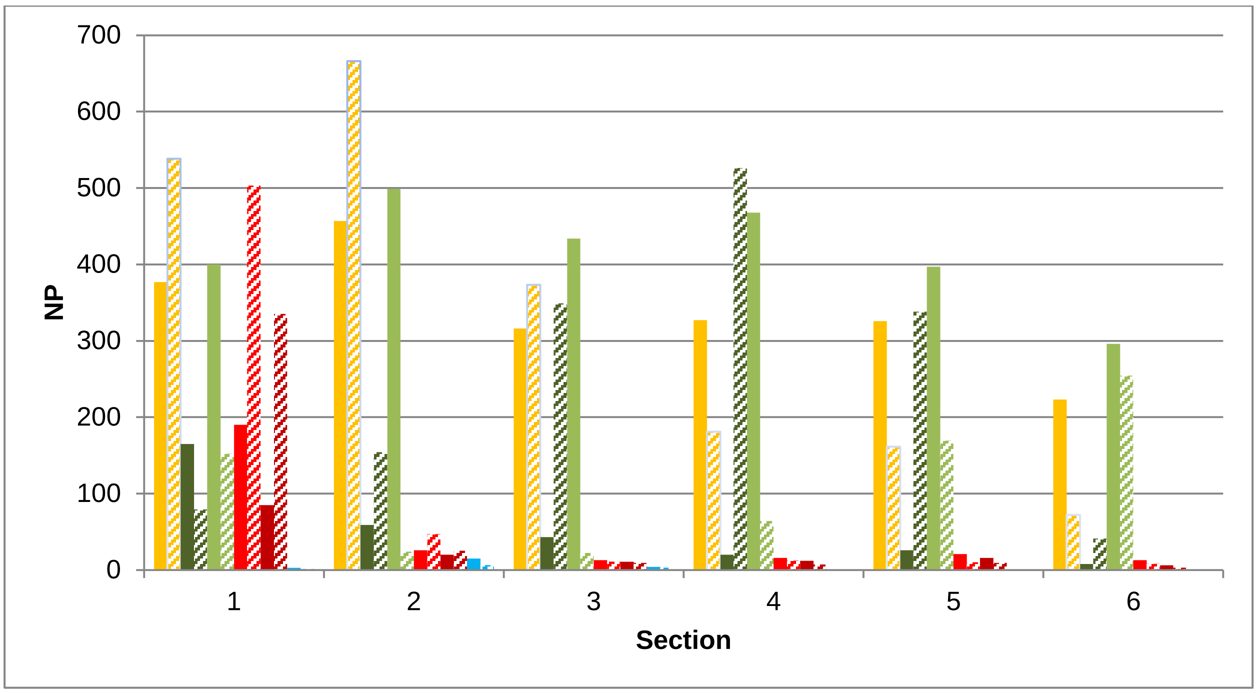

Figure 26. Number of patches (NP) - transect 2 – 1986 (solid) and 2013 (patterned) (legend figure 18).

Overall the number of patches in the entire transect remained roughly the same (figure 28). However, large changes within sections and classes did occur. The number of patches of the urban classes nearly tripled in section 1 and more than doubled in section 2. This was because the urban area in section 1 was not only larger, but also more fragmented in 2013 than it was in 1986. The increase in section 2 was simply the result of the increase in urban area in that section. However, in sections 3 to 6 the number of urban class patches decreased. This was the result of a decrease in urban area in those sections (see figures 21 to 24).

The most important change was the large decline in the number of light vegetation patches and the large increase in dense vegetation patches. This was caused by the large increase in light vegetation that in 2013 were present in large contiguous patches, particularly in the first 4 sections (figures 19 to 22). Dense vegetation on the other hand saw a large decline in land cover and the large patches present in 1986 fragmented or completely disappeared in 2013. The exception to this was the top left corner of section 1 and the bottom part of section 6 where forest reserves were present. The increase in the number of bare soil, road, grassy field patches in section 1 was attributed to the increase in that class' land cover (figure 25). However, in sections 2 and 3 the class' land cover decreased while the number of patches increased. This was because the increase in light vegetation had fragmented some of the large contiguous patches present in 1986 (figures 20 and 21). The decline in sections 4 to 6 was attributed to the decrease in land cover of the class.

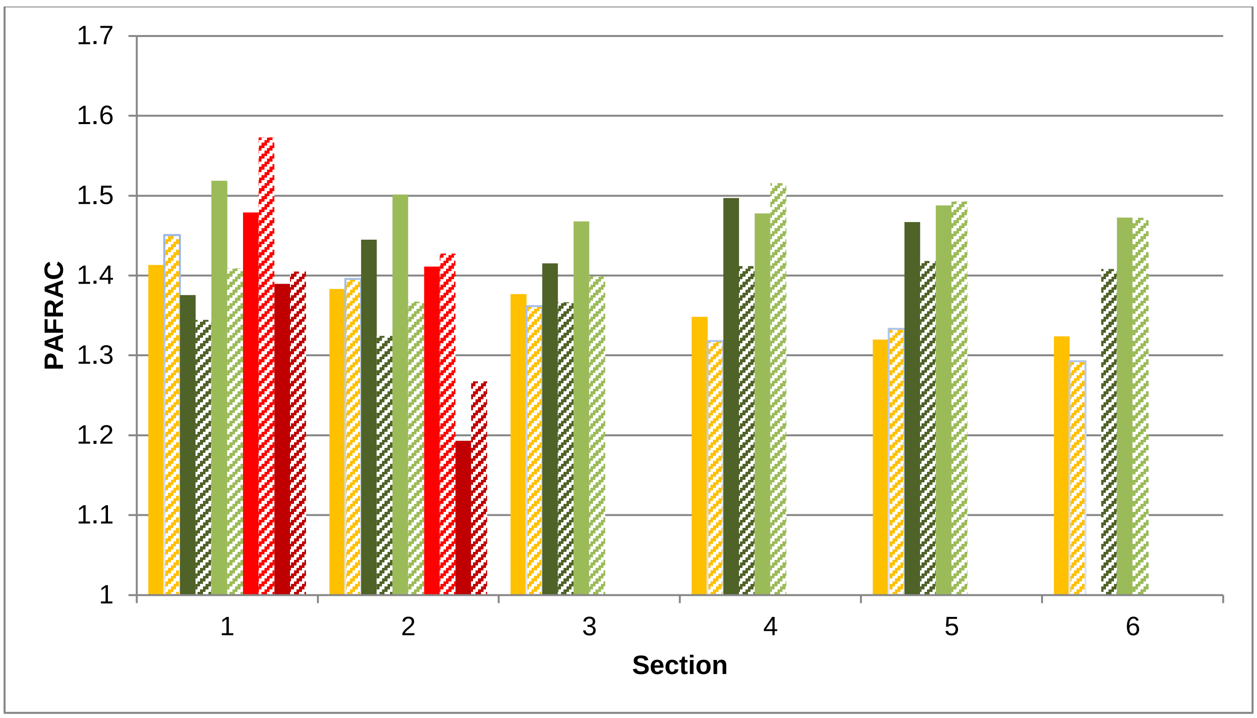

Figure 27. Perimeter Area Fractal Dimension (PAFRAC) - transect 2 – 1986 (solid) and 2013 (patterned) (legend figure 18).

The decrease of the PAFRAC of light vegetation in sections 1 to 3 was caused by the large increase in land cover of this class in these sections. The light vegetation formed large contiguous patches and these large patches have a relatively simpler shape, reducing the PAFRAC. The decrease in the PAFRAC of dense vegetation was harder to explain. The large contiguous patches present in 1986 were fragmented in 2013 with the exception of the forest reserves mentioned earlier. In general this should lead to an increase in PAFRAC. It is possible that the PAFRAC of sections 4 and 5 in 1986 was not accurate as the number of patches was quite low (20 and 26 respectively, see figure 26 and the appendix). However, this was not the case for sections 1 to 3. Here the most likely explanation is that the dense vegetation was clustered, leading to relatively simple shapes and a lower PAFRAC. This was most obvious in section 1 where most dense vegetation was in or near the forest reserve in the northwest corner (figure 19).

The urban with vegetation class showed a large increase in PAFRAC between 1986 and 2013 in section 1. This was explained by the increase in urban area in that period (figure 25). The urban areas with vegetation in 1986 increased in density and are largely classified as urban without vegetation in 2013. The new urban with vegetation patches were scattered over a large area (figure 19). As a consequence the PAFRAC of the urban without vegetation class remained almost unchanged over time. The large increase in the urban without vegetation class that was seen in section 2 could be caused by an underestimation of the PAFRAC in 1986 as it was based on only 25 patches. However, in 2013 the edge of the main urban area was seen in the top of section 2. As this edge was quite fragmented it is likely that the increase in the PAFRAC of the urban without vegetation class was actually caused by an increase in small patches with a relatively complex shape.

5.2.2. Landscape metrics transect 2

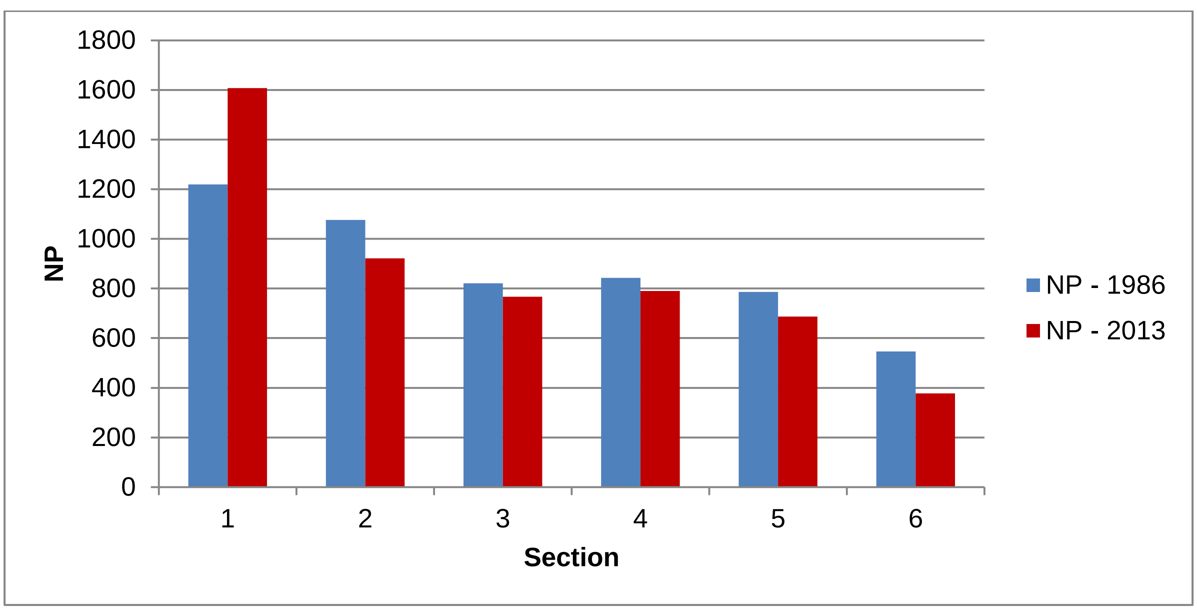

Figure 28. Number of patches (NP) - transect 2 – 1986 and 2013.

The total number of patches in 2013 was slightly lower than in 1986 in all sections even though the landscape had changed drastically. This was explained by the fact that one dominant land cover class (dense vegetation) had been replaced with another even more dominant land cover class; light vegetation (figure 18 and figure 25). The exception was section 1 (figure 19). Here the NP increased by almost 25%. This can be explained by the growth of the urban area from 1986 to 2013. The outskirts of this urban area was fragmented leading to a high number of additional patches when compared to 1986.

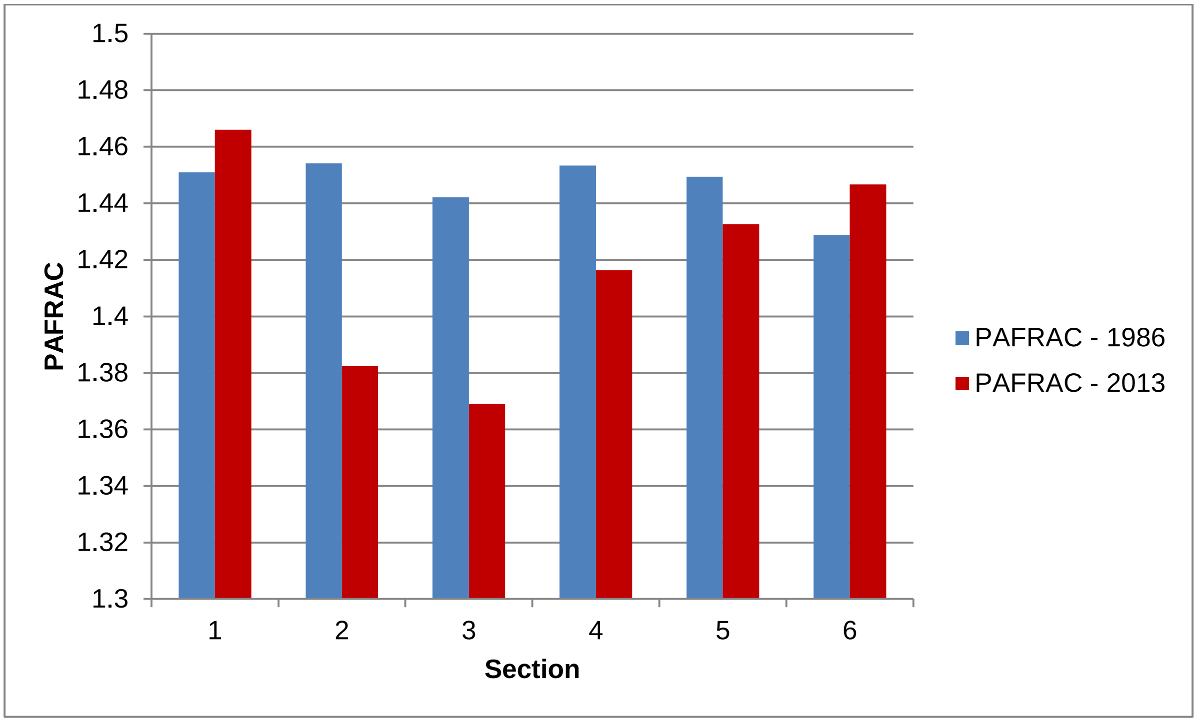

Figure 29. Perimeter Area Fractal Dimension (PAFRAC) - transect 2 – 1986 and 2013.

The PAFRAC in sections 2 to 4 was a lot lower in 2013 than in 1986. The reason for this was the existence of large contiguous areas of light vegetation in 2013 (figures 20 to 22). In section 1 the PAFRAC in 2013 was slightly higher than in 1986. This can be explained by the fragmented outskirts of the main urban area in that section (figure 19). Small patches generally have a more complex shape leading to a higher PAFRAC. This increase was not offset by the existence of the large contiguous areas of light vegetation that were also present in this section in 2013. In section 5 the PAFRAC remained almost the same even though the land cover changed greatly. The reason that the PAFRAC did not change by much as well was that while the amount of dense vegetation decreased it was still mostly found in large contiguous areas. Another reason was that the light vegetation that replaced the dense vegetation was also found in large contiguous areas (figure 23). In section 6 the PAFRAC is higher in 2013 than in 1986. This was caused by a moderate decline in dense vegetation that was mostly replaced by light vegetation. This led to a large number of complex patches (figure 24) that resulted in a higher PAFRAC, despite the decrease in total patch numbers in this section (figure 26).

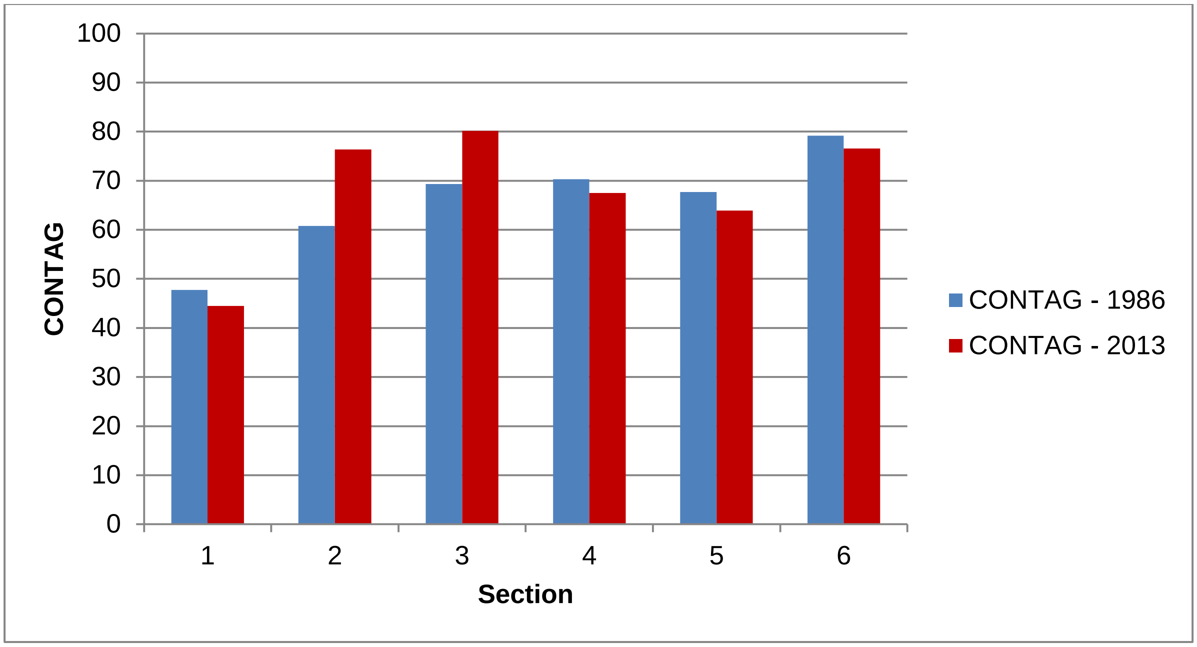

Figure 30. Contagion Index (CONTAG) - transect 2 – 1986 and 2013.

The CONTAG was slightly lower in sections 1, 4 and 5. In these sections the dominant land cover class (dense vegetation) was mostly replaced by light vegetation. However, light vegetation was not as dominant as dense vegetation was (figure 25). This led to fewer large contiguous patches where a large number of internal cells would result in a high CONTAG value. However, in sections 2 and 3 light vegetation was more dominant in 2013 than dense vegetation was in 1986. Just a handful of light vegetation patches covered the majority of these two sections, this led to a higher contagion value. In section 6 the dominant land cover was still dense vegetation, but light vegetation had increased in size at its expense. This led to a decrease in contagion.

5.3. Comparison of changes in PLAND in both transects

The largest difference in PLAND was seen in the vegetation classes. In transect 1 there was an increase in dense vegetation in the first two sections at the expense of light vegetation and bare soil, road, grassy field (figure 12). In transect 2 this was completely different. Light vegetation had almost completely replaced dense vegetation (figure 25). The exception was the forest reserve in the southern part of the transect (figure 24). The large difference in vegetation changes between the two transects point to a radically different development trajectory of the areas. More can be read about this in the discussion.

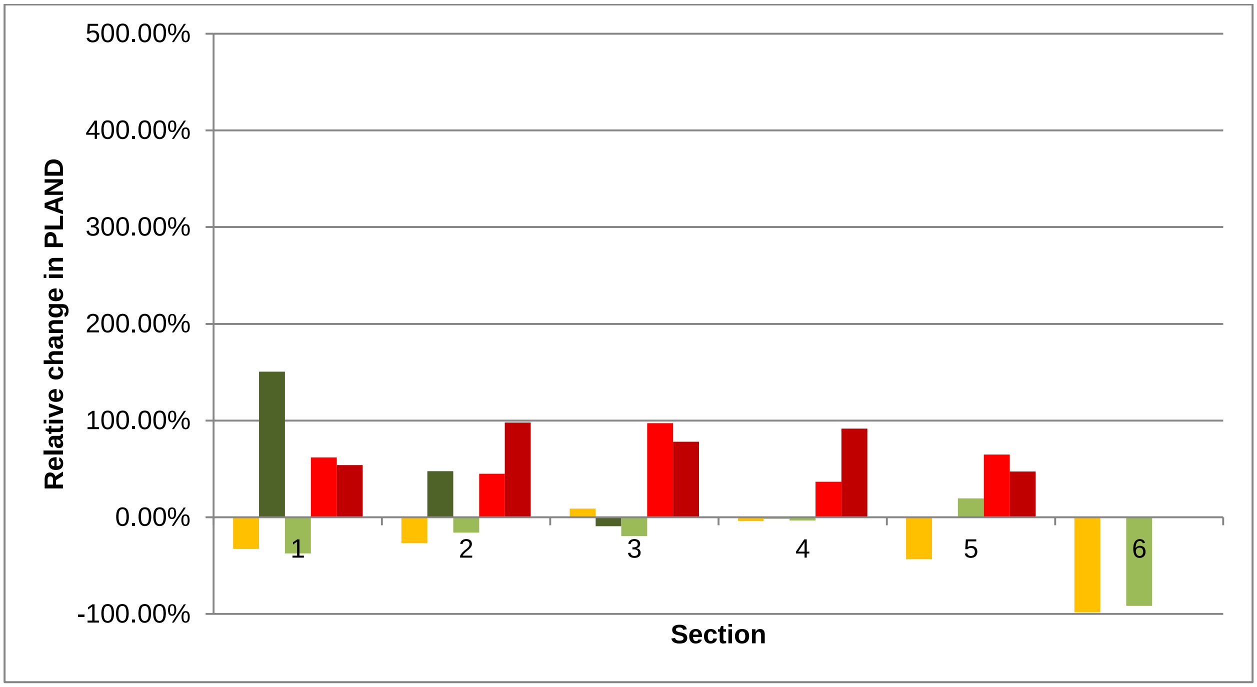

*Figure 31. Relative change in percentage land cover (PLAND). Transect 1 – ((PLAND 2013 divided by PLAND 1986)-1)*100%.*

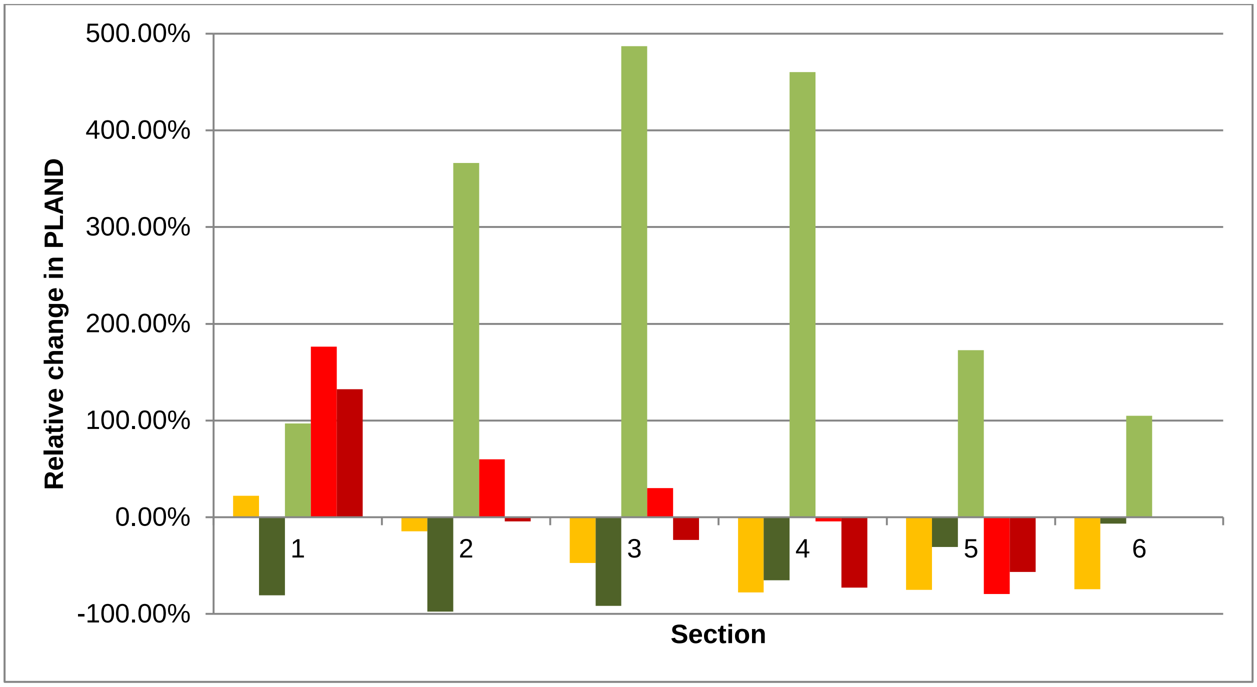

*Figure 32. Relative change in percentage land cover (PLAND). Transect 2 – ((PLAND 2013 divided by PLAND 1986)-1)*100%.*

Overall the changes in transect 2 were far greater than in transect 1. In both transects the main urban area greatly increased in size, but the increase was far larger in transect 2 (149% vs. roughly 80%). Overall there was a decrease in the bare soil, road, grassy field class for both transects, but it was relatively larger in transect 2 (24% vs. 17%). This decrease was likely caused by the overall increase in NDVI from 1986 to 2013 (table 6). Part of the bare soil, road, grassy field patches were classified as light vegetation due to this increase. This was especially the case for transect 1 which saw an overall NDVI increase of 0.1.

In transect 2 a decrease in urban areas was seen in all sections, except the main urban area located in section 1 and partly in section 2. This was not the case in transect 1. As mentioned in the section below figure 25 this could be caused by people moving from rural areas to cities in transect 2.

5.4. Human influence in the landscape

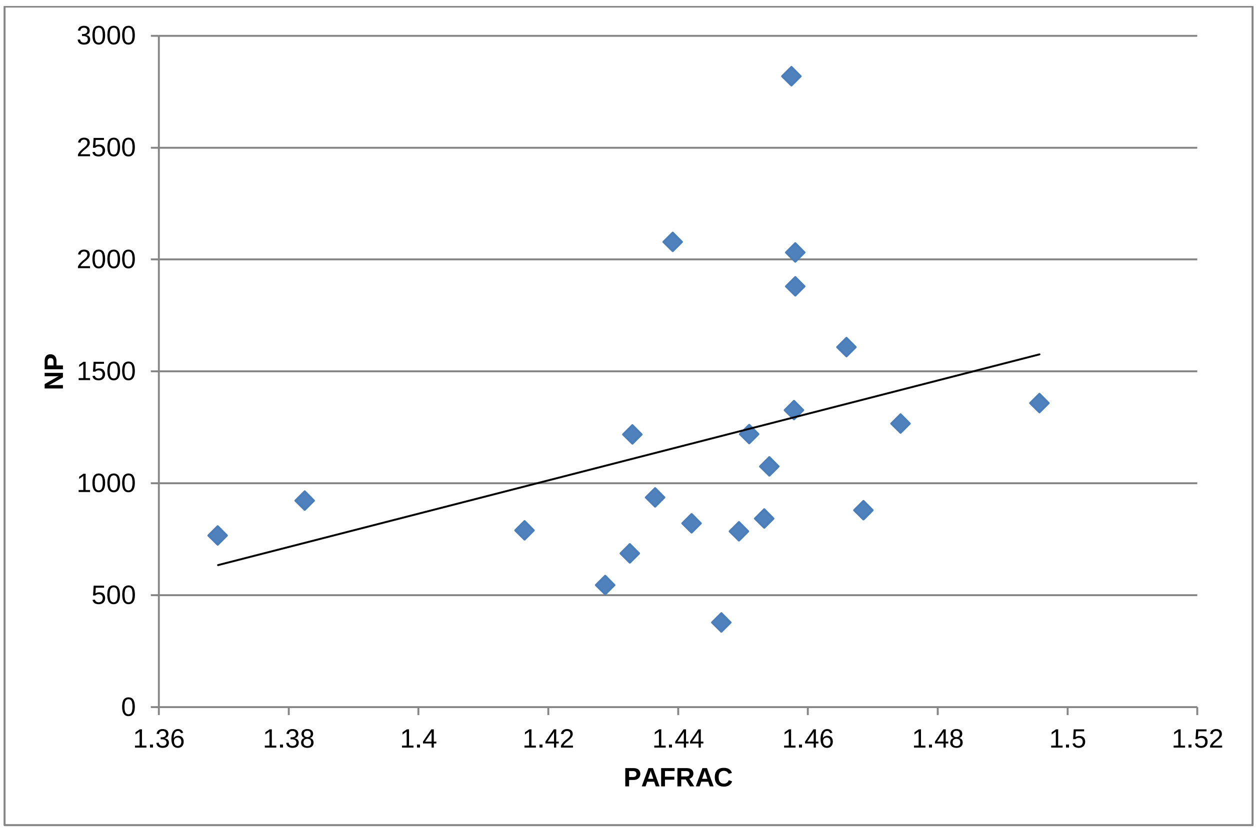

Figure 33. Perimeter Area Fractal Dimension (PAFRAC) vs. Total number of patches (NP) for each section of both transects in 1986 and 2013.

There is a moderate positive correlation between the PAFRAC and the NP (r = 0.36) (figure 33). This is in line with literature that states that a more fragmented landscape leads to smaller, geometrically more complex patches (McGarigal, 2014). The graph was influenced by a number of outliers, but removal of these outliers had little effect on the correlation (r = 0.36). The reason for the two leftmost outliers (PAFRAC 1.37 and 1.38) was that these metrics were from a section that was dominated by a very small number of large patches of a single class. These patches were interspersed by patches from other classes, but the result was still dominated by those large patches with a relatively simple shape. This led to a low PAFRAC. The high NP outlier (NP = 2819) with a relatively low PAFRAC (1.4575) was from transect 1 2013, section 2. This was the location of the main urban area, it is possible that despite the fragmentation of the landscape the shapes are less complex due to human influence.

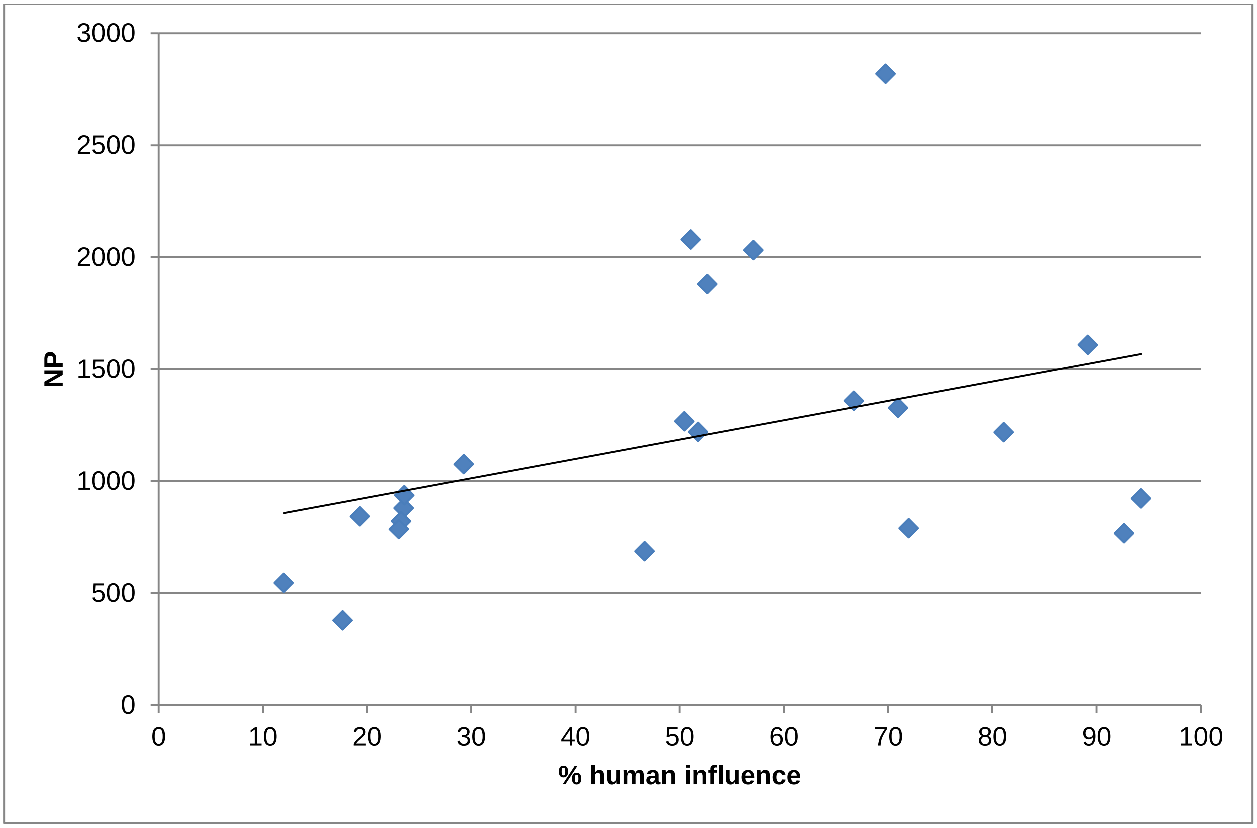

Figure 34. Total number of patches (NP) vs. the percentage of human influence on the landscape for each section of both transects in 1986 and 2013.

There is a moderate positive correlation between the NP and the percentage human influence (r = 0.39) (see section 4.6). This is an indication that human influence leads to a fragmentation of the landscape. However, there were several outliers in the data that influenced the trend.

When looking at the relative change in NP versus the relative change in percentage human influence no clear relation became apparent (r = 0.16 for landscape 1 and r = 0.06 for landscape 2) (figure 35). From this data the conclusion was drawn that no clear relation between NP and percentage human influence existed.

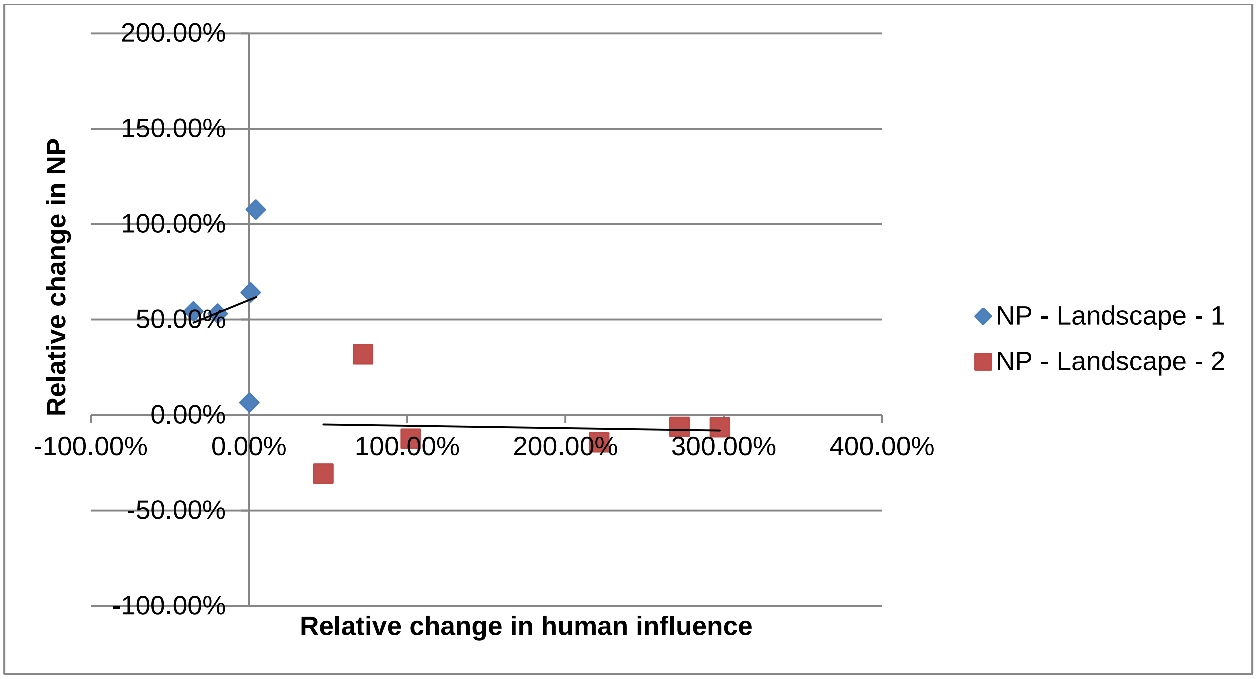

Figure 35. Relative change in number of patches (NP) vs. relative change in human influence percentage in the landscape for each section of both transects in 1986 and 2013.

PAFRAC has a moderate negative correlation with % human influence (r = -0.32). This indicates that a higher % human influence led to a lower PAFRAC.

This trend was greatly influenced by the two outliers in the bottom right of the graph. Removal of these outliers led to a weak positive correlation. However, no clear reason existed for removal of the outliers as both outliers had a NP (767 and 922) that was far above the number needed to get a useful PAFRAC result (>20) (McGarigal, 2014). It is possible that these outliers are due to the percentage of human influence consisting almost entirely of light vegetation, rather than a mix of classes as was the case for the other sections. However, two sections are not enough to draw that conclusion.

It seems that human influence led to a lower PAFRAC and a higher NP. Though how much of an effect human influence has was not possible to determine based on the amount of data available and the outliers present in the current data.

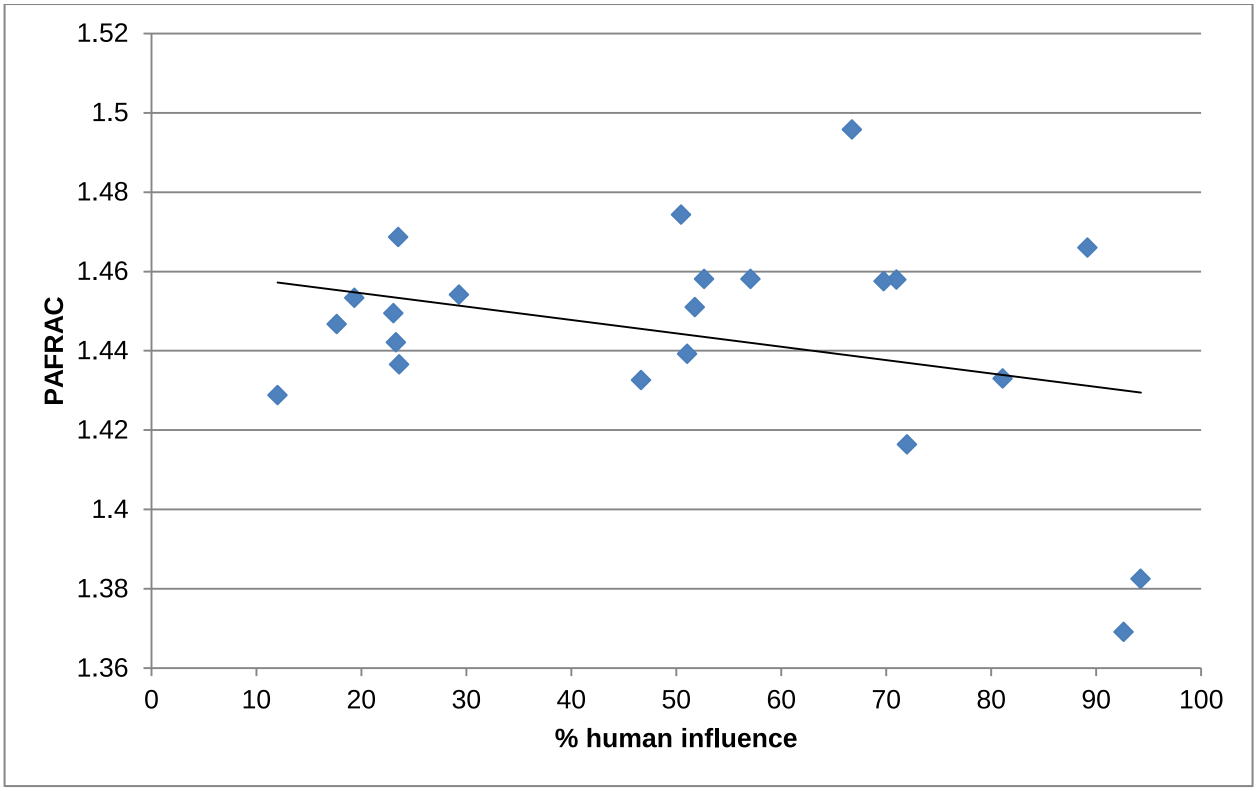

Figure 36. Perimeter Area Fractal Dimension (PAFRAC) vs. the percentage of human influence on the landscape for each section of both transects in 1986 and 2013.

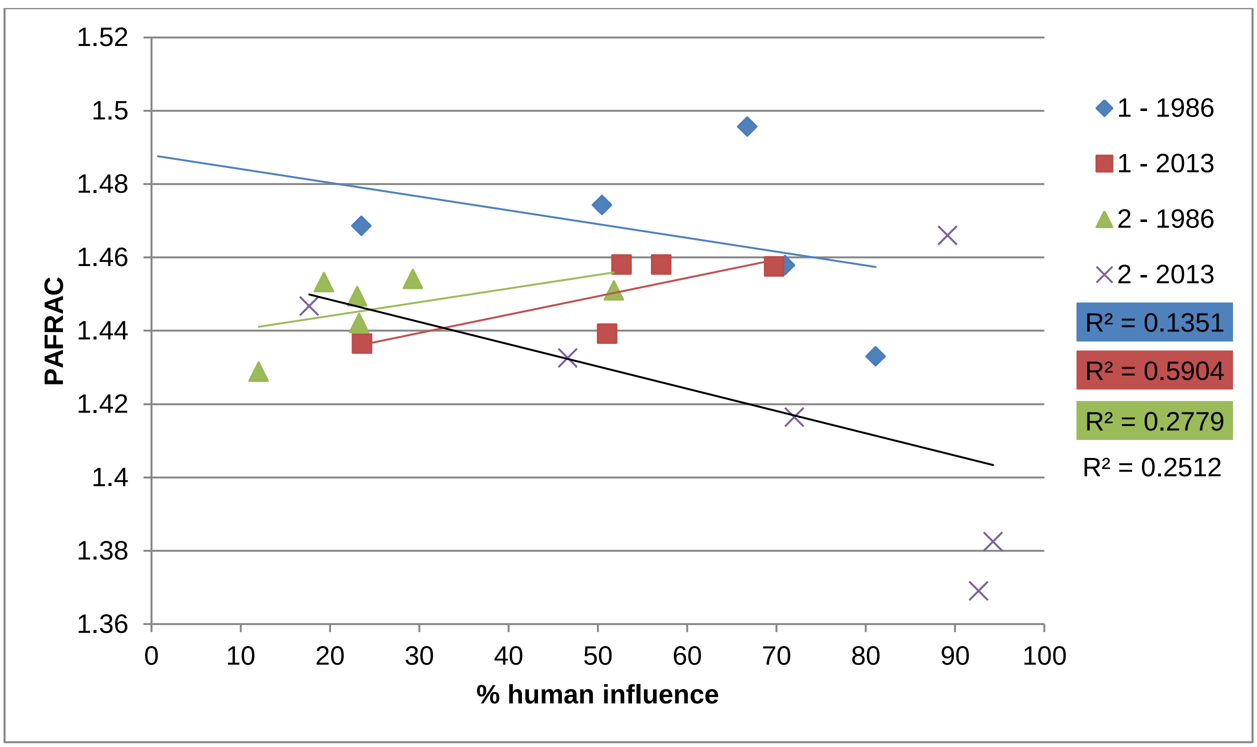

Figure 37. Perimeter Area Fractal Dimension (PAFRAC) vs. the percentage of human influence on the landscape for each section of both transects in 1986 and 2013 plotted separately.

To ensure that no trends in the individual transects and times were missed they were plotted separately in figure 37. Transect 1 had 5 points for each year and transect 2 had 6 points per year. The reason is that no meaningful results for PAFRAC could be calculated for transect 1 section 6 due to the very low number of patches.

While the R^2's are quite high, as is to be expected with just 5 or 6 data points, no overall trend could be seen in the data. The conclusion is that there was no clear relation between the percentage of human influence and PAFRAC that held for either or both transects.

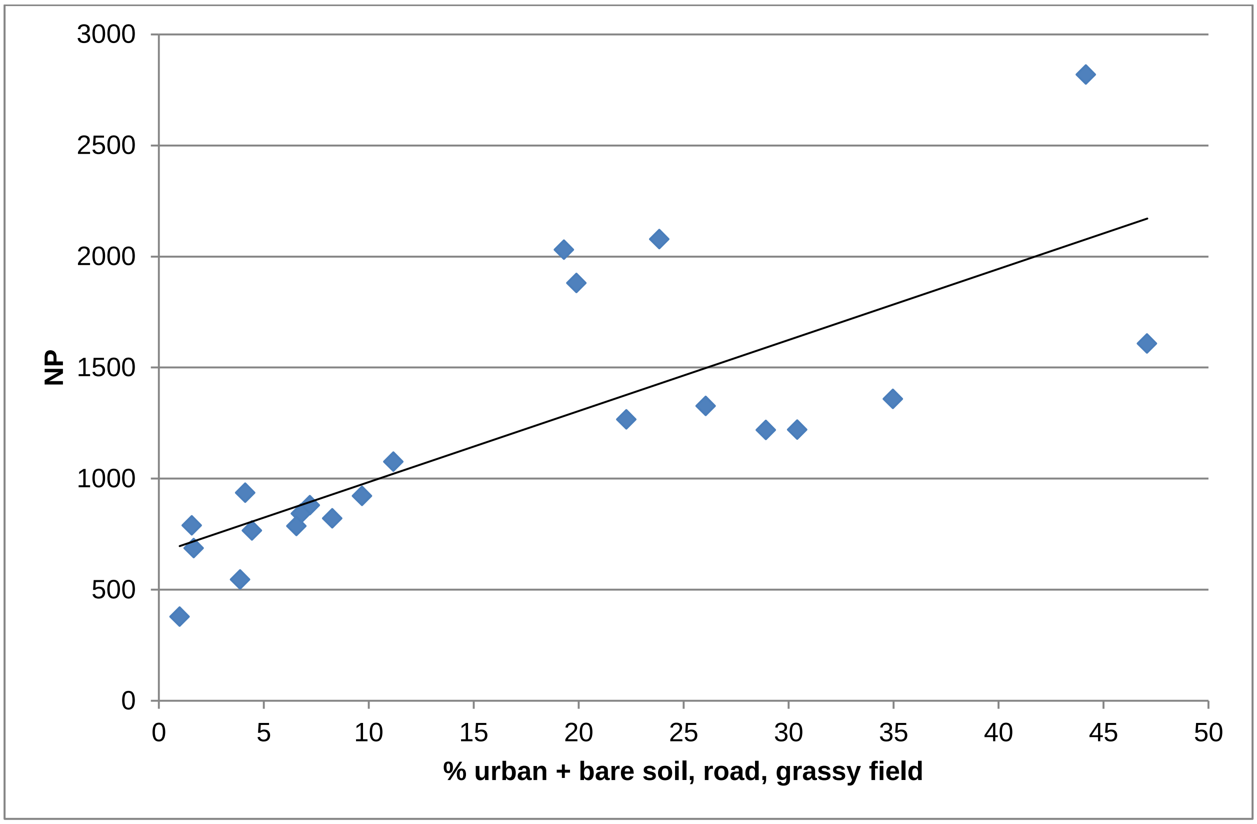

Figure 38. Total number of patches (NP) vs. % urban + bare soil, road, grassy field (%UB) in the landscape for each section of both transects in 1986 and 2013.

It is highly likely that both the light vegetation and the bare soil, road, grassy field classes contained at least some natural patches. Therefore it was decided to determine whether plotting % urban with vegetation + urban without vegetation + bare soil, road, grassy field (%UB), % urban with vegetation + urban without vegetation + light vegetation (%UL) and % urban with vegetation + urban without vegetation against NP and PAFRAC would yield different results.

There is a strong correlation between %UB and NP (r = 0.77). From figure 38 it is obvious that this correlation is particularly strong when the %UB was low. The higher the %UB the less clear the relation becomes. The conclusion is that there is a strong relation between %UB and NP when the %UB was low. However, this relation becomes unclear for a %UB of 15 and higher. To determine if this relation holds for both transects and times figure 39 was made. From this figure it is clear that this relation indeed holds for every transect and time.

When looking at the relative change in NP versus the relative change in %UB the correlation became even stronger (r = 0.96 for landscape 1 and r = 0.83 for landscape 2) (figure 40).

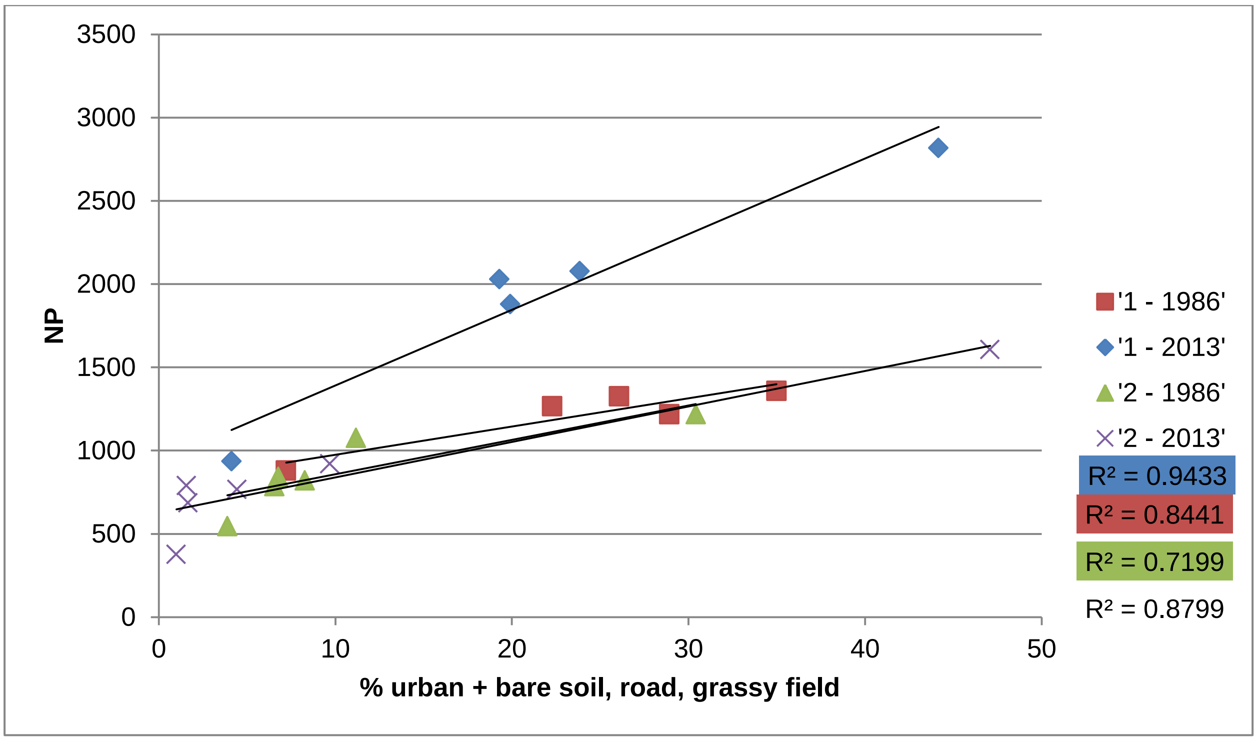

Figure 39. Total number of patches (NP) vs. % urban + bare soil, road, grassy field (%UB) in the *landscape for each section of both transects in 1986 and 2013 plotted separately.*

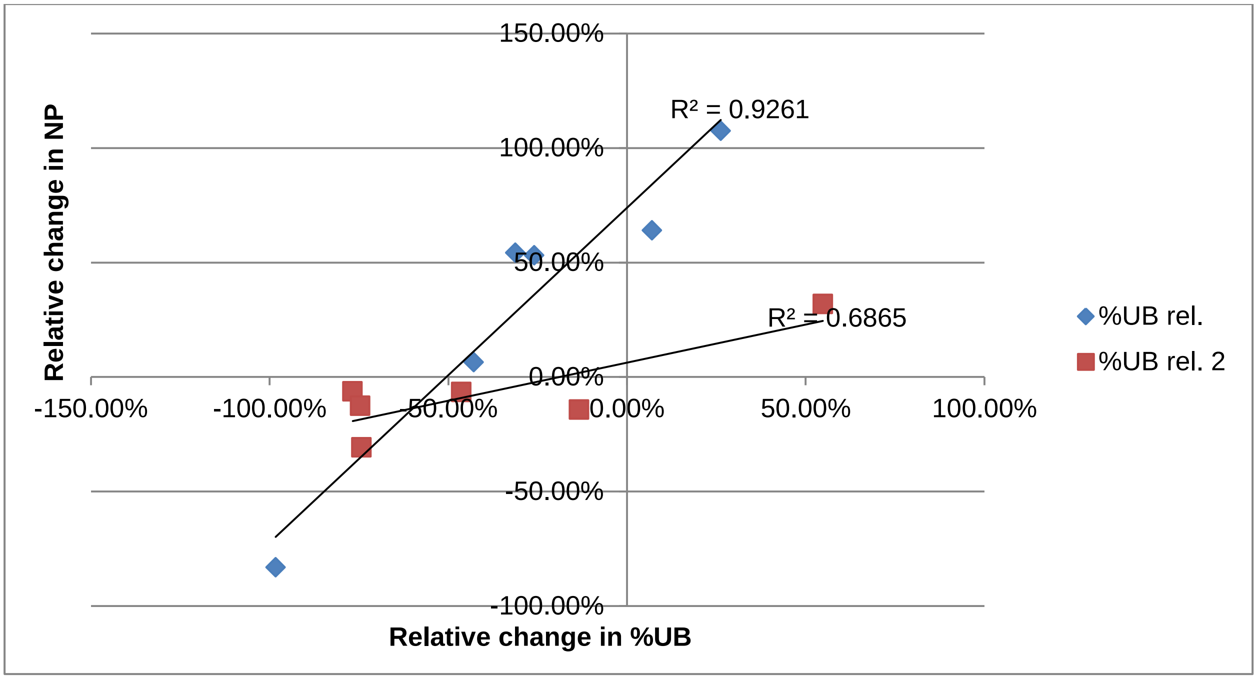

Figure 40. Relative change in total number of patches (NP) vs. relative change in the % urban + bare soil, road, grassy field (%UB) in the landscape for each section of both transects in 1986 and 2013.

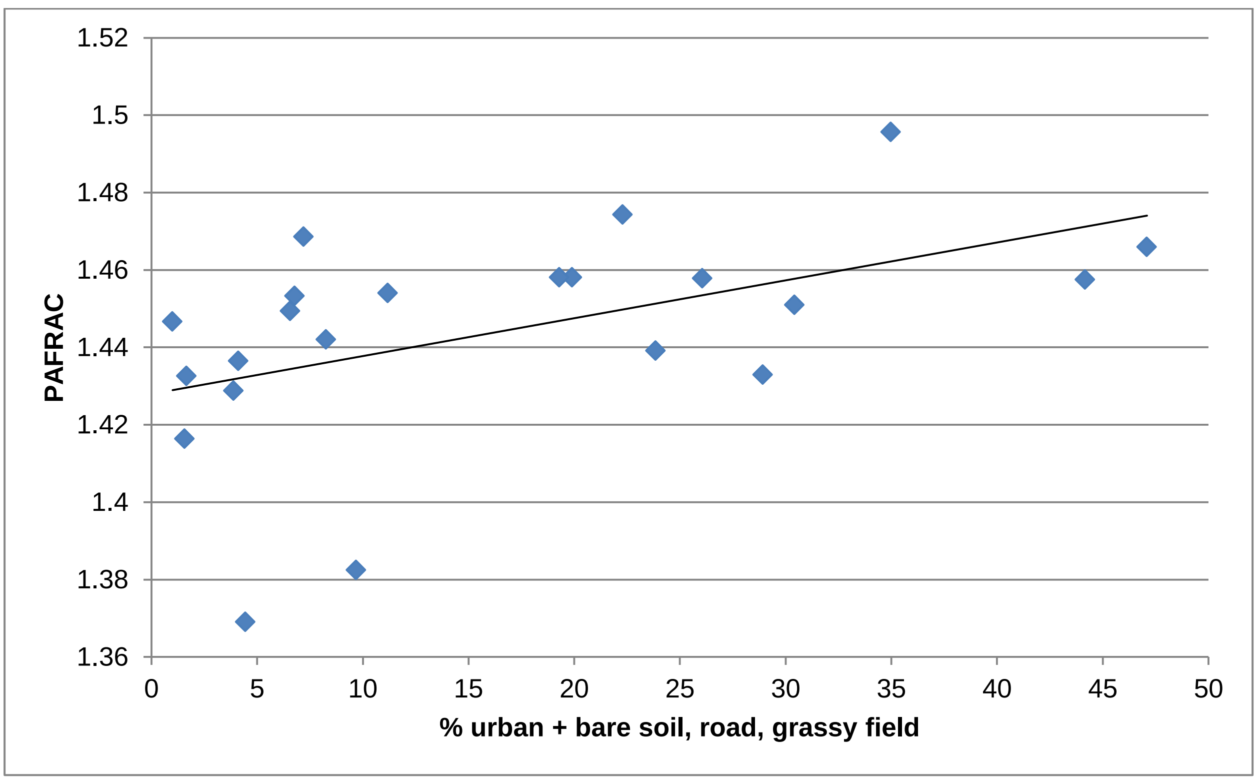

Figure 41. Perimeter Area Fractal Dimension (PAFRAC) vs. % urban + bare soil, road, grassy field (%UB) in the landscape for each section of both transects in 1986 and 2013.

%UB has a moderate positive correlation with PAFRAC (r = 0.49) (figure 41). The conclusion is that there is a relation between the two variables. This relation seemed to be influenced by the two outliers in the bottom-left of the graph. However, removal of these two outliers only led to a slight increase in the correlation (r = 0.53).

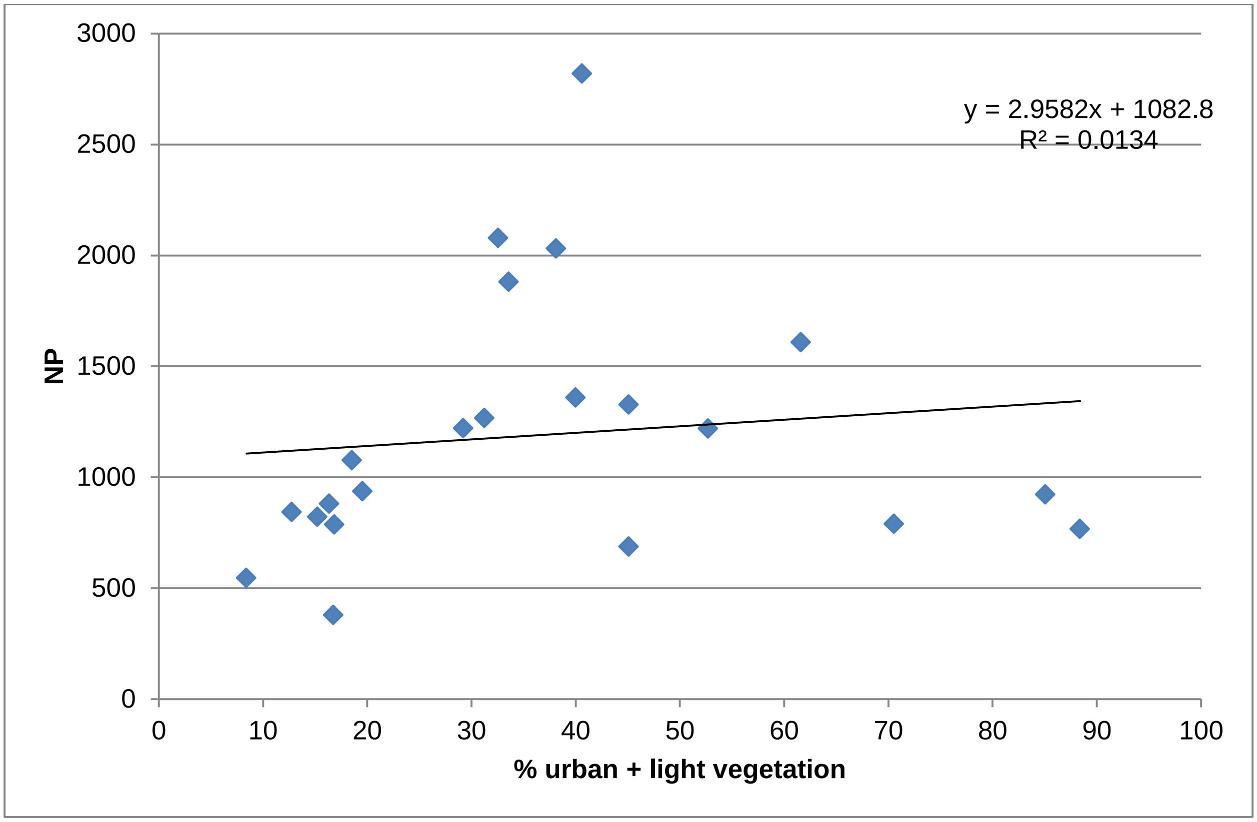

Figure 42. Total number of patches (NP) vs. % urban + light vegetation (%UL) in the landscape for each section of both transects in 1986 and 2013.

There is a very weak positive correlation between % urban + light vegetation (%UL) and NP (figure 42). The large spread in the data made it impossible to draw conclusions from this graph.

There is a strong negative correlation between %UL and PAFRAC (-0.58) (figure 43). However, the two outliers between 85 and 90 %UL have a large effect on the trend so more data is required before a conclusion can be drawn.

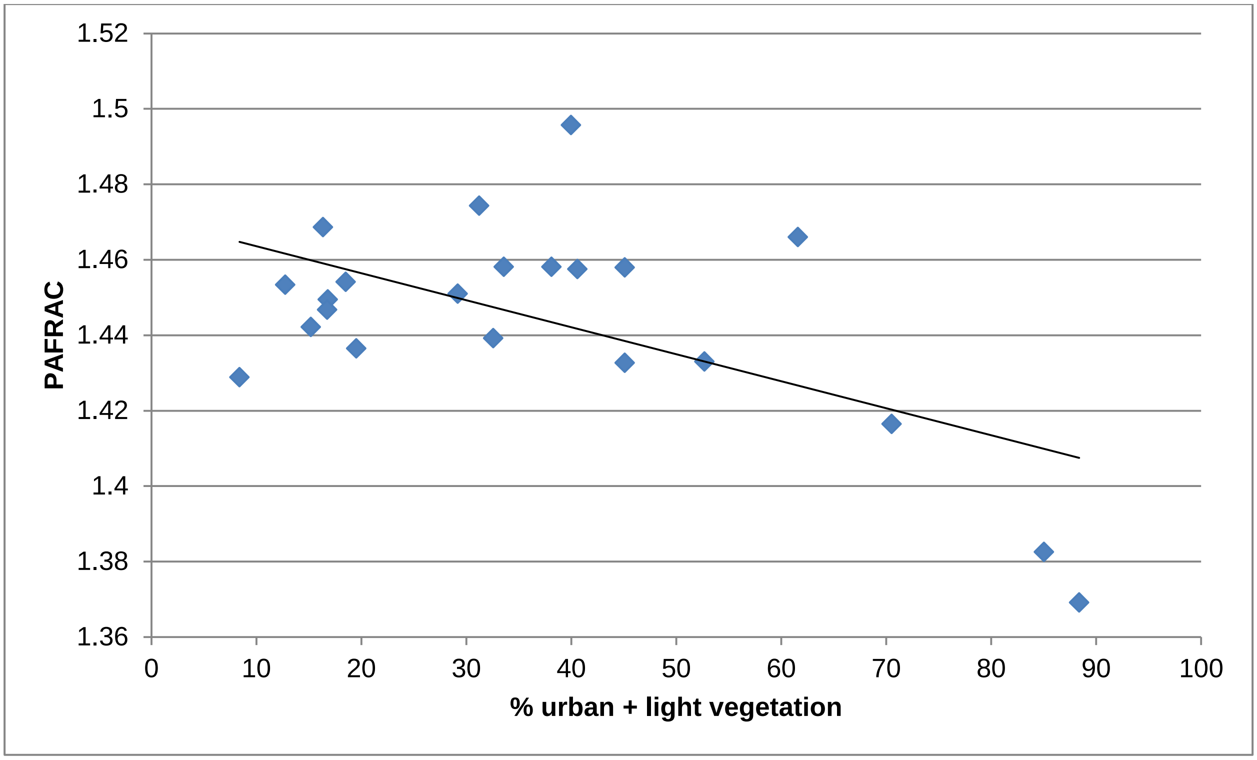

Figure 43. Perimeter Area Fractal Dimension (PAFRAC) vs. % urban + bare soil, road, grassy field (%UB) in the landscape for each section of both transects in 1986 and 2013.

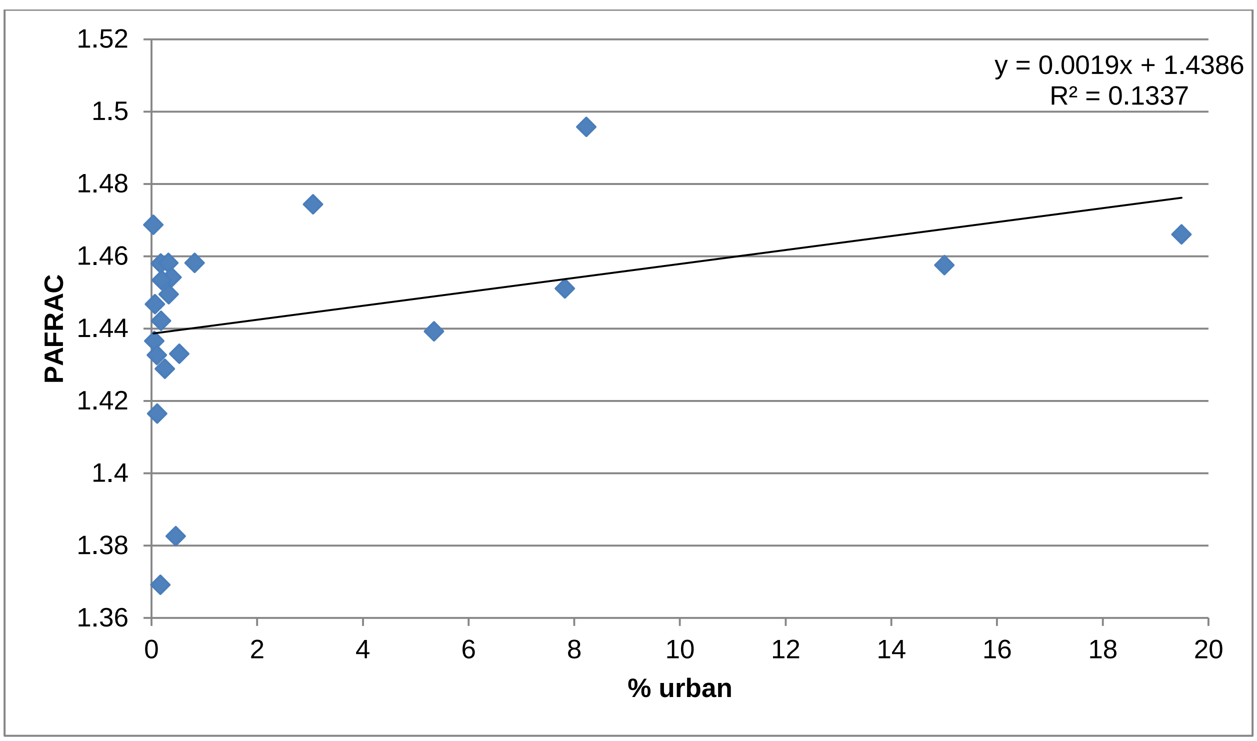

Figure 44. Total number of patches (NP) vs. % urban in the landscape for each section of both transects in 1986 and 2013.

With a moderate positive correlation (r = 0.37) it was concluded that there is no relation between the %urban and PAFRAC (figure 44).

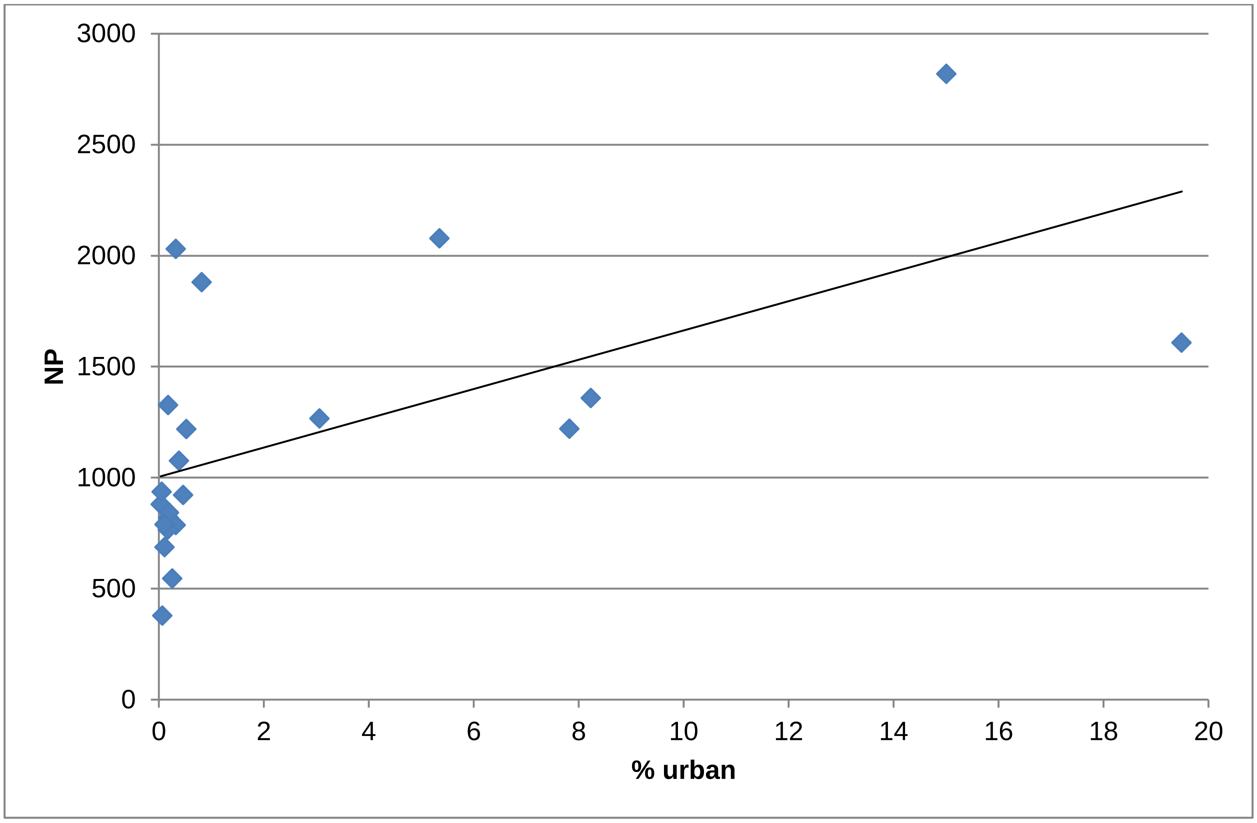

Figure 45. Total number of patches (NP) vs. % urban in the landscape for each section of both transects in 1986 and 2013.

While the correlation is quite high (r = 0.6), figure 45 shows that there is no clear relation between % urban and the NP. Excluding low percentages of urban area from figure 44 and 45 could prove useful. However, more data is needed to draw meaningful conclusions, as the amount of sections with higher percentages of urban area were limited and their spread in NP was quite large.

6. Discussion

6.1. Results

The results show that the transects had several trends in common: a large overall increase in urban area land cover, an overall decrease in the land cover of bare soil, roads and grassy fields (figure 12 and 25) and an overall decrease in PAFRAC. All other land cover classes and the total number of patches (NP) showed large differences between the two transects (figure 31 & 32 and figure 16 & 28).

Transect 1 showed an increase in urban area of 79% and transect 2 an increase of 122%. These large increases in urban area were as expected, because both transects are located in countries with a high population growth. Sierra Leone and Guinea have had population growths of more than 2% per year over the past few decades (World Bank, 2015). The overall decrease in bare soil, roads and grassy fields (17% in transect 1 and 24% in transect 2) was likely caused by the overall increase in NDVI from 1986 to 2013 (table 6). Many bare soil patches became vegetated from 1986 to 2013 as a spot-check showed. The difference in NDVI was not simply the result of changing land cover, as it was also observed in the forest reserves where the land cover did not change. A possible explanation for the overall increase in NDVI is that the Sahel drought diminished from the 1990s and onward (Sahel Precipitation Index, 2013). The Sahel region is located just north of the transects so it is possible that large climate changes in the Sahel could also influence the transects. Further research is needed to test this hypothesis as it is beyond the scope of this research. It is possible that the NDVI in both regions increased due to simultaneous changes in the local climate, however the transects are located roughly 200km apart so this is not as likely.

In transect 1 from 1986 to 2013 almost all urban areas increased in size (by 50-82%) and dense vegetation increased at the expense of light vegetation. However, in the same period in transect 2 only the main urban area increased in size (by 149% in section 1 and 20% in section 2) and the urban areas in all other urban areas decreased in size (by 7% to 74%). This could be the result of people moving to the cities from rural areas. At the same time the amount of dense vegetation drastically declined and was replaced by light vegetation. This points to a radically different development of both transects. While beyond the scope of this research a possible explanation for the differences is the economic development of countries the transects are located in: Guinea (transect 1) and Sierra Leone (transect 2). The GDP per capita of Guinea has seen only a very small increase of 40% from 1986 to 2013. The GDP per capita of Sierra Leone on the other hand greatly increased from 1986-2013 and in 2013 was roughly 400% higher than in 1986 (World Bank, 2015)(figure 46). A rapid increase in GDP per capita can be seen from 2000. This was likely because the Sierra Leone Civil War that lasted from 1991 to 2002 had mostly ended in 2000. Further research is needed to test this hypothesis.

Figure 46. GDP per capita (in current US$) for Guinea and Sierra Leone from 1986 to 2013 (World Bank, 2015).

The overall decrease in PAFRAC seen in both transects (figures 16 and 29) is unlikely to have had the same cause. The decrease in PAFRAC in transect 2 is likely linked to the decrease in NP as larger patches generally have a more simple shape. However, the same does not apply to transect 1 because there was a decrease in PAFRAC and a simultaneous increase in NP. From literature it followed that the drop in PAFRAC was linked to human influence in transect 1 as this can lead to simpler shapes in a more fragmented landscape. However, figure 36 and 37 show that this was not the case in either of these two transects. Transect 1 showed a decrease in PAFRAC with increasing human influence in the landscape in 1986, but an increase in PAFRAC with increasing human influence in 2013. In transect 2 this was completely opposite. Therefore the conclusion is that PAFRAC is not a useful landscape metric to determine human influence in the landscape. This is in contrast to a study by O'Neill et al. (1997) that states that in general human influence lowers the PAFRAC because humans simply the landscape.

There was another large difference in the NP. In transect 1 a relatively large increase in patches was seen in all sections except 6 (figure 15). However, in transect 2 a decrease in the NP was seen in the entire transect except in the first section where the main urban area was located (figure 28). The reason is that transect 2 was dominated by light vegetation in 2013 and this led to a small number of very large patches. Transect 1 on the other hand featured very few large patches and this actually decreased from 1986 to 2013. The cause of this large difference is likely the different economic development of the areas (figure 46).

PAFRAC proved to be not useful for estimating human influence in an area. NP showed more promise (figure 34), but there was no correlation between the relative change in NP and the relative change in percentage human influence (35). However, when human influence was defined as all classes, except water, dense vegetation and light vegetation (%UB) there was a clear relation between NP and %UB (figure 38). There was also a strong correlation between %UB and NP ($r = 0.77$) for each individual transect and time (figure 39), as well as a strong correlation between relative change in NP and relative change in %UB (figure 40). This makes fragmentation (NP) a far more useful landscape metric to estimate human influence in an area. It is important to note that vegetation, and thus agriculture, is not included in this definition of human influence.

6.1. General issues

One of the main challenges when dealing with OBIA is that the method relies on expert knowledge. This is particularly true for comparison to the 'ground truth'. In this research the ground truth was a combination of the Landsat images and Google Maps. As no Google Maps images existed for 1986 the ground truth for that year was based solely on the Landsat images.

It is likely that there were Google Maps images available for the region in 2013. However, the ground truth for 2013 is based on images taken in 2015. It is certain that changes occurred in the intermediate years. These changes could lead to errors in the segmentation and classification parts of the research. Regardless it was decided that the benefits of adding high-resolution imagery to the ground truth would outweigh the drawbacks.

The choice of the transect size was arbitrary and solely based on image availability. Transect 2 required a length of 60km to range from urban area to undisturbed nature. The 10km width was decided based on enclosing the entire main urban areas of the transect and to make the division into sections easier.

6.2. Images

Ideally one would pick transects that range from fully urban to undisturbed nature. This way the effect of human influence on landscape patterns can be determined across a wide range of landscapes. This would also make comparison of the transects easier.

It was decided to focus the research on West Africa as changes in the landscape over the last few decades have been rapid and extensive and it is an area where malaria is endemic. This made it easier to detect changing landscape patterns and would also allow the application of any new insights to similar landscapes in the region.

As the research focused on landscape pattern changes it was important to obtain multiple sets of images taken in the same years and as close to the same date as possible. This led to some problems during the image acquisition phase. Finding two sets of images with little to no cloud cover, for two years (ideally at least 10 years apart), and roughly the same dates, proved difficult. In the end two sets of images were found, but some compromises regarding the transects had to be made. In both transects the undisturbed nature is a forest reserve. So for both transects the transition from a human influenced landscape to a natural landscape is relatively abrupt. This will limit the information obtained on the spatial patterns and the effect of human influence on landscape patterns in this ‘transition zone’.

6.3. Segmentation

In literature several segmentation approaches were found, however, these methods were based on the use of high-resolution imagery. This research used only Landsat imagery with a resolution of 30m and for that reason the parameter values found in literature were not suitable. For example Maxwell (2010) used various segmentation parameter settings, with the scale value ranging from 20 to 200. The parameter settings with the lowest scale value was tested to determine if it was suitable for this research. The parameter values that were used: shape = 0.1, compactness = 0.9 and scale = 20. The result of this was unsatisfactory. The segmentation was too coarse and made it impossible to differentiate between light and dense vegetation among others (figure 46).

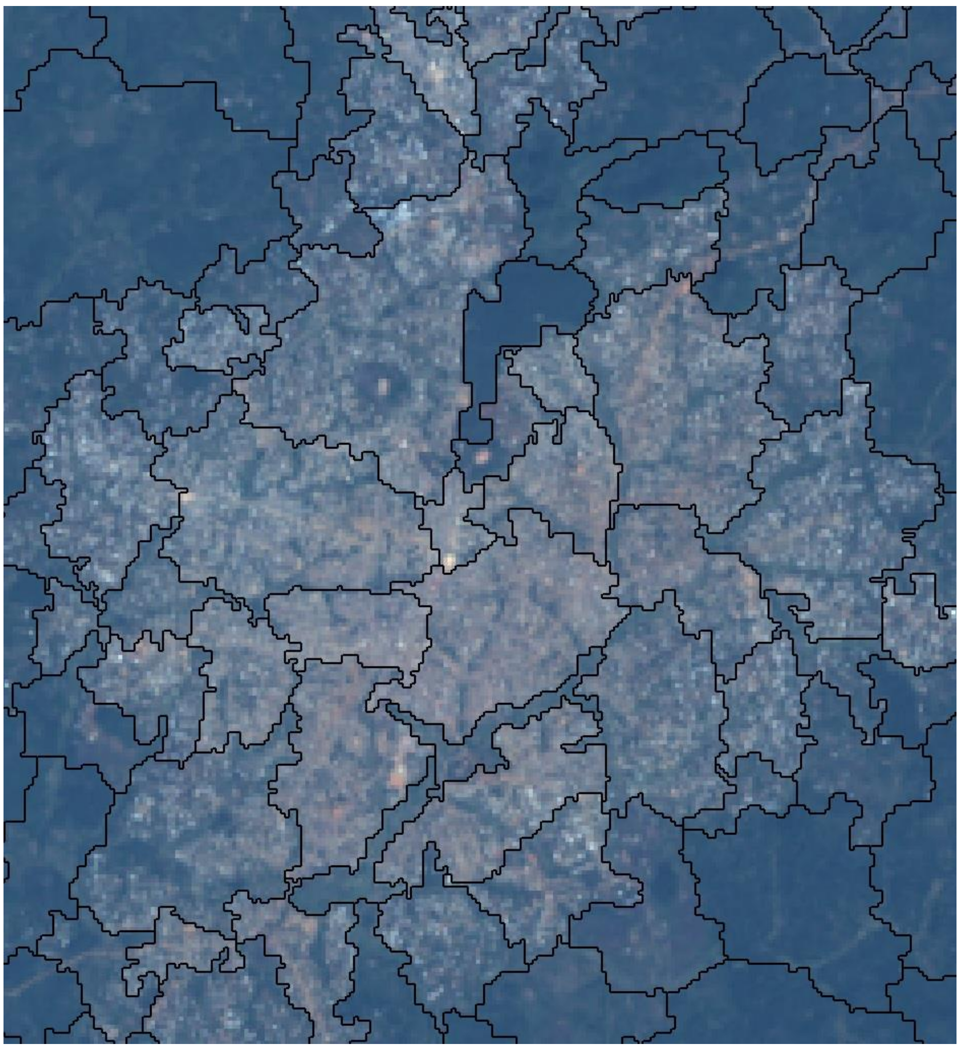

Figure 46. Segmentation of the main urban area of transect 1 – 2013 (true colour) using the parameter values from Maxwell (2010): shape = 0.1, compactness = 0.9 and scale = 20.

For this research different parameter values were used that placed no significance on the shape of the object and a far lower scale value (see 4.2). This led to better segmentation results based on visual inspection and comparison to the ground truth (figure 47). Future research would benefit from using a robust methodology to determine the best parameter values, rather than trial and error combined with visual inspection. Being able to use shape in the segmentation of the images would likely lead to better delineated objects. Therefore the usage of higher resolution imagery (where possible) is highly recommended.

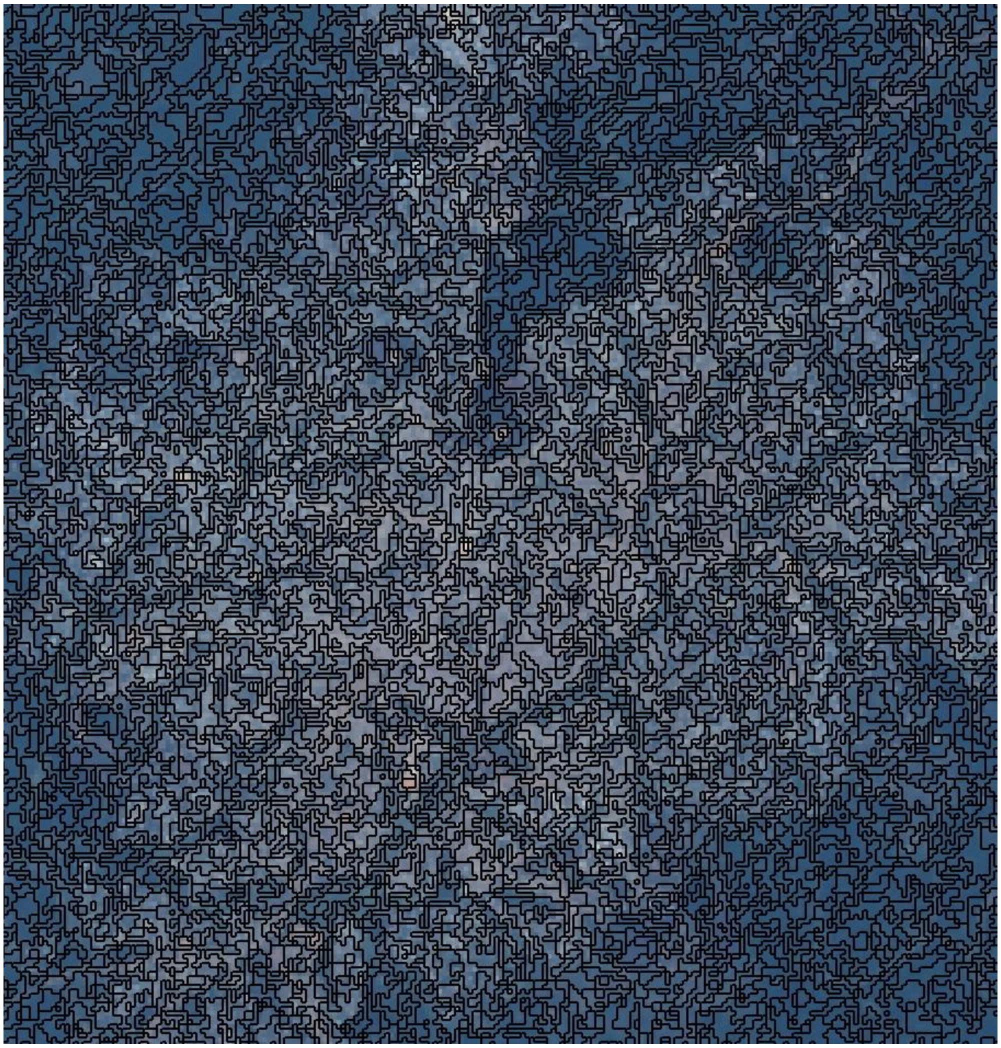

Figure 47. Segmentation of the main urban area of transect 1 – 2013 (true colour) using the parameter values used in this research: shape = 0 and scale = 2 (compactness has no influence if the shape value is zero).

6.4. Classification

Only six classes were chosen as the resolution proved to be a limiting factor in distinguishing more classes. Part of the research included finding a method to determine human influence from landscape patterns. Therefore classes were chosen in such a way that they could either be considered human influenced or natural. Dense vegetation and water were assumed to be the natural state of this landscape. All other classes were assumed to be human influenced. This assumption was based on the fact that the nature preserves in this area all consist of dense vegetation (forest).

However, it is important to note that this is a generalization. Light vegetation, grassland or even bare soil could be natural in this area due to, for example, grazing or forest fires.

The most problematic issues of classification were determining the thresholds between similar classes. These thresholds were determined based on visual inspection and are generally in line with accepted values in literature.

Distinguishing between dense vegetation and water on the one hand and the other classes on the other hand was important for the classification. This is because determining what percentage of the landscape was influenced by humans relies on correctly classifying the natural part of the landscape (dense vegetation and water). However, changing the NDVI threshold for dense vegetation by just 0.01 will have an effect on the PLAND while still passing visual inspection. This adds uncertainty to the percentage human influence statistic.

Several changes were made to account for the higher overall NDVI in 2013 in transect 1 (table 6). The method from transect 1 1986 was applied to transect 2, but again some changes were made to account for the overall change in NDVI. However, after these changes were made the method of transect 2 1986 gave satisfactory results for the same transect in 2013. The changes were few and fairly simple. This points to a relatively robust method for the simple classification of a landscape. However, this also means that expert knowledge is still required to apply the methods to a new landscape. This makes the process more time-consuming and more prone to errors.

The main roads in the transects were mostly distinguishable, but the smaller roads leading into the countryside were not. These smaller roads were often dirt roads and overgrown in many areas. Distinguishing between roads, bare soil, fallow fields, construction sites and other non-vegetated areas proved impossible. Therefore it was decided to combine into one class: bare soil, roads and grassy fields. Unfortunately this will make it impossible to distinguish between objects that were most definitely human influenced, such as roads, and those which may have been caused by human influence, such as bare soils. Developing a way to solve this problem was outside of the scope of this research, but could prove useful for further research.

Classification errors were seen throughout the research area (an example can be seen in figure 48). These errors were caused by three issues: 1. Image objects that were not correctly delineated. 2. The resolution of 30m led to a large number of mixed pixels 3. The threshold values gave satisfactory results when looking at the entire transect, but led to some classification errors in certain areas. A higher resolution would diminish these classification errors, though eliminating them will likely prove to be impossible. These classification errors are unlikely to greatly affect the results as this research is about large-scale landscape patterns.

However, there is one case where the classification errors did affect the results. Usually an increase in city population not only increases the area of a city, but also its density. However, the main urban area of transect 1 was more fragmented in 2013 than in 1986 despite a large increase in population between those years. Precise numbers could not be found, but in 2004 the population was 128,402 and in 2013 188,463 according to the official census. This makes it likely that the population was far lower than 128,402 in 1986.

The cause of this contradiction is that the classification of the main urban area in transect 1 – 1986 had some problems, causing it to look less fragmented than it really was (figure 48).

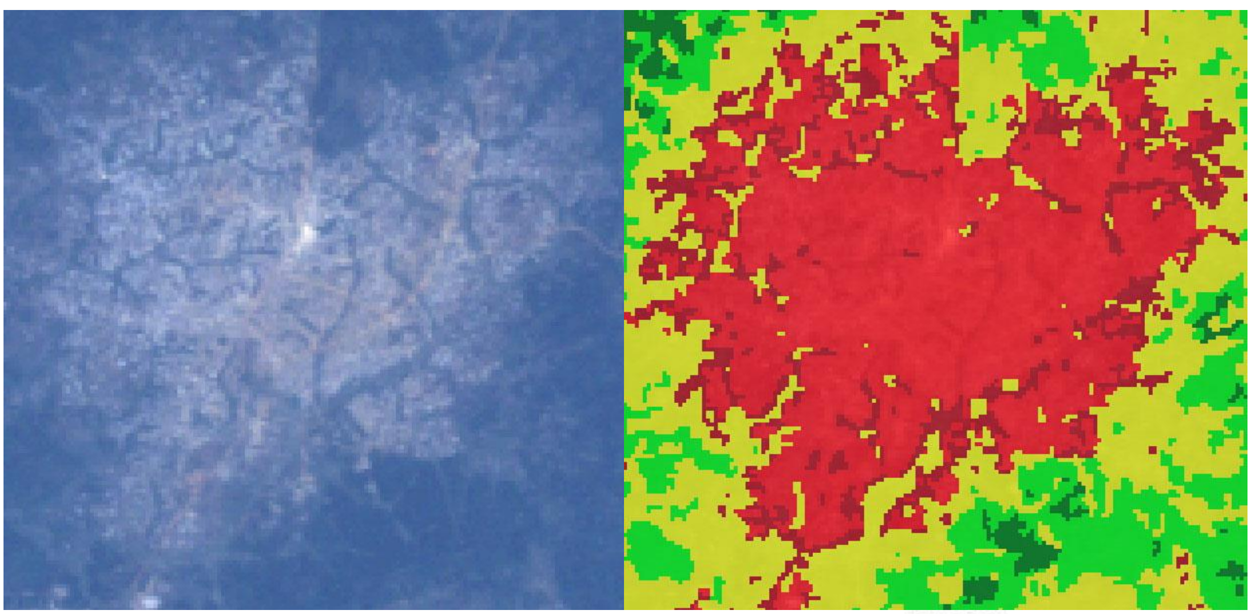

Figure 48. Classification errors in the main urban area of transect 1 – 1986. Some of the ‘channels’ seen in the unclassified image on the left (true colour) are classified as urban no vegetation rather than bare soils or urban with vegetation (seen on the right).

6.5. Analysis

A mix of landscape and class metrics was chosen that combined would give information on composition and configuration. Only a small number of the hundreds of metrics available were chosen to limit the overlap between the metrics. It is likely that using more metrics would have resulted in a better analysis, though it also likely that there are diminishing returns on including additional metrics. That is why it was decided to focus on a handful of metrics that were deemed the most informative.

The landscape metrics were calculated for arbitrary sections. It is possible that changing these borders would influence the results and conclusions. Increasing the number of sections would increase the number of data points in the tables and graphs. However, the underlying amount of data would not change. So while it might be easier to detect trends in the data, it would also reduce the accuracy of every data point as it would be based on fewer patches. Making sure that the main urban area of transect 1 was located in a single section would have given the PLAND a larger range.

It was not possible to calculate PAFRAC for every section and class, because 20 patches are needed for a meaningful result (McGarigal, 2014). Increasing the size of the sections would likely reduce the number sections with fewer than the 20 patches needed for meaningful PAFRAC results. This can be done by either reducing the number of sections per transect, or by increasing the size of the transect, while keeping the number of sections constant.

7. Conclusions

The landscape patterns and their changes through time and space were compared for two transects in West Africa that contained both highly urbanized areas and heavily forested natural areas using Object Based Image Analysis (OBIA). It was also determined to what extent it is possible to use landscape patterns to determine human influence in an area.

7.1. Trends and differences in spatial patterns

Several trends and differences were seen in the spatial patterns in the two transects through time and space. The urban land cover in both transects roughly doubled in size between 1986 and 2013 (79% for transect 1 and 122% in transect 2), as was expected for a region with a rapidly increasing population. In transect 1 the urban areas in all sections increased by 50-82%. However, in transect 2 a decrease of 7% to 74% in urban area was seen in all sections, with the exception of the main urban area that increased in size by 149%. It is likely that this was caused by a people moving from rural areas to the main urban area in transect 2.

Transect 1 showed an increase in dense vegetation, even in the vicinity of the main urban area (figure 5). The opposite was true for transect 2 (figure 18). Here dense vegetation almost disappeared around the main urban area, with the exception of the nearby forest reserve. Generally the further away from the main urban area, the smaller the decrease in dense vegetation was in this transect. Still there was a large decrease even when close to the forest reserve in the southern-most part of the transect. When combined with the difference between the transects in the development of the urban areas it points to a radically different development trajectory of the two transects. The most likely cause is that the economy of Sierra Leone (transect 2) showed a far higher growth from 1986 to 2013 than Guinea (transect 1) (figure 46).

The bare soil, road, grassy field class decreased by 17% in transect 1 and 24% in transect 2. As a general increase in Normalized Difference Vegetation Index (NDVI) was seen in both transects it is highly likely that part of the bare soil patches became vegetated between 1986 and 2013. A spot-check showed that this was the case. The forest reserves showed the same general increase in NDVI, despite an unchanged land cover. Therefore the cause of this general increase in NDVI is likely a change in (local) climate as both transects were affected despite being roughly 200km apart. The Sahel drought diminished from the 1990s and onward and this region is located just north of the study areas. The large change in climate (particularly precipitation) in the Sahel has likely influenced the areas of the transects as well. Further research is needed to determine this.

A large increase in landscape fragmentation was seen in transect 1 based on the Total Number of Patches (NP). This was not the case for transect 2 where the NP actually decreased in all sections, except in section 1 where the main urban area was located. The reason for this difference is that transect 2 showed a massive increase in light vegetation from 1986 and 2013 (100% to 500%) (figure 32). This led to several very large patches, reducing the NP. In transect 2 the changes were not nearly as pronounced, the largest increase was a 150% increase in dense vegetation in section 1 (figure 31).

An overall decrease in Perimeter Area Fractal Dimension *(*PAFRAC, a measure of patch shape complexity) was seen for both transects from 1986 to 2013. The decrease in PAFRAC in transect 2 can be linked to the decrease in NP as larger patches generally have a simpler shape. However, the same does not apply to transect 1 because there is a decrease in PAFRAC and a simultaneous increase in NP.

7.2. Estimation of human influence by using landscape patterns

From literature it followed that the drop in PAFRAC seen in transect 1 was linked to human influence as this generally leads to simpler shapes in a more fragmented landscape. However, no correlation between PAFRAC and the percentage of the landscape influenced by humans (defined as all land cover except dense vegetation and water) could be found (figure 36 and 37). It was concluded that PAFRAC was not useful to estimate human influence in the landscape.

NP on the other hand showed more promise (figure 34), but no correlation between the relative change in NP and the relative change in human influence was found (figure 35). However, using a different definition of human influence (all land cover except dense vegetation, light vegetation and water: %UB) a strong correlation between NP and %UB was found ($r = 0.77$, figure 38). This correlation was also seen for each individual transect and time (figure 39) and for the relative change in NP vs. the relative change in %UB (figure 40). Therefore the estimation of human influence in the landscape is best done through a measure of fragmentation, rather than PAFRAC. However, it is important to note that vegetation is not included in the %UB definition, so agriculture in the area is not seen as human influence.

Overall the PAFRAC for both transects decreased even when the NP increased. An increase in NP generally leads to an increase in shape complexity as smaller patches have relatively complex shapes. This is an indication that the human influence in the research areas has greatly increased as humans have a tendency to simplify the landscape. However, with the current data it is not possible to use landscape patterns to estimate the human influence in an area.

7.3. General conclusions

Using OBIA on Landsat images led to fairly accurate classification results based on visual inspection of current satellite images. Using shape in the segmentation process did not improve the results. This was most likely because the 30m resolution of Landsat was not sufficient to correctly identify the relatively small agricultural fields and grazing areas that make up a large part of the landscape. This subsequently hindered the classification of the images. Therefore to make full use of OBIA higher resolution imagery is needed for research in this region.

The classification method developed is fairly robust as relatively few changes were needed to use the method of transect 1 on transect 2. However, expert knowledge was still required even when applying the method to a fairly similar landscape.

Classification errors were mostly the result of incorrectly delineated image objects, mixed pixels and the threshold choices that were made. Classification errors due to incorrectly delineated image objects and mixed pixels can likely be reduced by using higher resolution images. However, the threshold choices will remain subjective to some degree.

To increase the accuracy of the methods and to be able to better determine the trends the size of the transects and/or the number of transects need to be increased. A combination of both is likely optimal as it would lead to methods that can be applied to a wider range of landscapes.

7.1. Recommendations

To better study the relation between landscape patterns and human influence a land use classification should be made, rather than the land cover classification that was used in this research. To be able to make a meaningful land use classification it has to be possible to distinguish between spectrally similar classes like agriculture and grassland, or dirt roads and natural open spaces. To that end it would be highly useful to be able to use shape as a part of the classification process. Unfortunately the segmentation process did not see any improvement from using shape. This is likely because a higher resolution than the 30m resolution of Landsat is needed to be able to correctly delineate the small irregularly shaped fields in this region. Subsequently it was not possible to use shape as a part of the classification process with the exception of roads and rivers in some parts. Therefore it is recommended to use images with a higher resolution than Landsat for future OBIA research in this region.

In this research the ground truth was a combination of visual interpretation of the 2013 Landsat images and Google Maps with images from 2015. For future research it would be useful to use high resolution images taken closer to the date of when the Landsat images were taken.

Future research should use malaria data to determine if it is possible to link landscape patterns to a change in malaria statistics. The focus should lie on landscape fragmentation because it showed the greatest correlation with human influence in the landscape and increasing human influence generally leads to an increase in mosquito breeding grounds.

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Appendices

Transect 1, 1986

Section	Class metrics: percentage land cover (PLAND)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	28.3993	18.8924	52.1807	0.1064	0.4212	0
2	25.8861	29.0145	44.9218	0.0536	0.1241	0
3	26.749	33.2509	31.7674	1.788	6.4448	0
4	19.2249	49.5327	28.1816	0.9463	2.1145	0
5	7.165	76.4812	16.3145	0.0054	0.0339	0
6	0.5085	99.265	0.2265	0	0	0

Transect 1, 1986

Section	Class metrics: number of patches (NP)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	614	404	172	20	9	0
2	661	371	281	5	9	0
3	554	255	399	106	45	0
4	534	150	487	70	26	0
5	373	77	426	2	2	0
6	75	1	49	0	0	0

Transect 1, 1986

Section	Class metrics: perimeter-area fractal dimension (PAFRAC)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	1.4263	1.4197	1.5218	1.6413	N/A	N/A
2	1.4292	1.4205	1.5471	N/A	N/A	N/A
3	1.4595	1.4518	1.5502	1.5952	1.3311	N/A
4	1.3957	1.4496	1.5285	1.5513	1.3678	N/A
5	1.3546	1.4131	1.5171	N/A	N/A	N/A
6	1.3515	N/A	1.3777	N/A	N/A	N/A

Transect 1, 1986

Section	Landscape metrics: NP, PAFRAC, CONTAGION, MSIEI			
	NP	PAFRAC	CONTAGION	MSIEI
1	1219	1.433	49.9437	0.5872
2	1327	1.4579	47.7258	0.647
3	1359	1.4957	39.1162	0.7745
4	1267	1.4743	47.5807	0.6309
5	880	1.4686	67.6085	0.3003
6	125	1.2564	96.4655	0.0134

Transect 1, 2013

Section	Class metrics: percentage land cover (PLAND)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	19.0854	47.3334	32.7609	0.1723	0.648	0
2	18.975	42.8952	37.8053	0.0778	0.2458	0.0009
3	29.1586	30.2335	25.5966	3.5299	11.4797	0.0018
4	18.4959	48.9355	27.2201	1.294	4.0544	0
5	4.0583	76.396	19.4867	0.0089	0.05	0
6	0.0085	99.9727	0.0188			0

Transect 1, 2013

Section	Class metrics: number of patches (NP)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	786	311	705	49	29	0
2	904	419	665	26	16	1
3	806	307	700	618	386	2
4	649	212	731	297	189	0
5	411	79	439	3	5	0
6	8	1	12	0	0	0

Transect 1, 2013

Section	Class metrics: perimeter-area fractal dimension (PAFRAC)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	1.39	1.4259	1.5334	1.4502	1.2849	N/A
2	1.3972	1.4453	1.516	1.3852	1.2717	N/A
3	1.4472	1.417	1.5294	1.5125	1.409	N/A
4	1.3835	1.4013	1.5061	1.4583	1.4199	N/A
5	1.28	1.4099	1.4739	N/A	N/A	N/A
6	N/A	N/A	1.2142	N/A	N/A	N/A

Transect 1, 2013

Section	Landscape metrics: NP, PAFRAC, CONTAGION, MSIEI			
	NP	PAFRAC	CONTAGION	MSIEI
1	1880	1.4581	47.1116	0.6214
2	2031	1.4581	52.2376	0.5657
3	2819	1.4575	39.4902	0.7597
4	2078	1.4392	43.939	0.653
5	937	1.4365	68.7158	0.2938
6	21	1.0651	99.7692	0.0005

Transect 2, 1986

Section	Class metrics: percentage land cover (PLAND)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	22.5867	46.6542	21.3817	2.9587	4.8692	1.55
2	10.7877	67.2836	18.141	0.1484	0.2383	3.401
3	8.08	76.027	15.0312	0.0566	0.1294	0.676
4	6.5729	80.6593	12.5717	0.0837	0.1125	0
5	6.2315	76.9383	16.5019	0.1448	0.1835	0
6	3.6221	87.9778	8.1439	0.0656	0.1905	0

Transect 2, 1986

Section	Class metrics: number of patches (NP)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	377	165	400	190	85	3
2	457	59	499	26	20	15
3	316	43	434	13	11	4
4	327	20	468	16	12	0
5	326	26	397	21	16	0
6	223	8	296	13	6	0

Transect 2, 1986

Section	Class metrics: perimeter-area fractal dimension (PAFRAC)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	1.4131	1.3756	1.5187	1.4791	1.3897	N/A
2	1.3831	1.4451	1.5015	1.4113	1.1933	1.493
3	1.3767	1.4153	1.4678	1.4765	1.1562	N/A
4	1.3484	1.497	1.4779	1.1966	1.1823	N/A
5	1.32	1.4669	1.4877	1.4789	1.1397	N/A
6	1.3239	N/A	1.4727	1.433	N/A	N/A

Transect 2, 1986

Section	Landscape metrics: NP, PAFRAC, CONTAGION, MSIEI			
	NP	PAFRAC	CONTAGION	MSIEI
1	1220	1.451	47.7697	0.6396
2	1076	1.4541	60.7638	0.3886
3	821	1.4421	69.3351	0.2785
4	843	1.4533	70.329	0.2482
5	786	1.4494	67.7256	0.294
6	546	1.4288	79.1649	0.1528

Transect 2, 2013

Section	Class metrics: percentage land cover (PLAND)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	27.5937	9.0129	42.1051	8.1769	11.3169	1.7944
2	9.2148	1.6673	84.591	0.2374	0.2284	4.0611
3	4.266	6.3833	88.2184	0.0737	0.0989	0.9598
4	1.4628	27.9981	70.4284	0.0801	0.0306	0
5	1.5559	53.3415	44.9929	0.0297	0.08	0
6	0.9284	82.3216	16.6825	0.0431	0.0243	0

Transect 2, 2013

Section	Class metrics: number of patches (NP)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	538	79	152	503	335	1
2	666	154	24	47	25	6
3	373	349	22	11	9	3
4	181	526	64	12	7	0
5	161	338	169	10	9	0
6	72	41	254	8	3	0

Transect 2, 2013

Section	Class metrics: perimeter-area fractal dimension (PAFRAC)					
	Bare soil, road, grassy field	Dense Vegetation	Light Vegetation	Urban with vegetation	Urban without vegetation	Water
1	1.4505	1.3441	1.4087	1.5726	1.405	N/A
2	1.3956	1.3243	1.3673	1.4272	1.2673	N/A
3	1.3614	1.3664	1.3988	1.3483	N/A	N/A
4	1.318	1.4117	1.5156	1.5027	N/A	N/A
5	1.3329	1.4179	1.4926	1.3257	N/A	N/A
6	1.2924	1.408	1.472	N/A	N/A	N/A

Transect 2, 2013

Section	Landscape metrics: NP, PAFRAC, CONTAGION, MSIEI			
	NP	PAFRAC	CONTAGION	MSIEI
1	1608	1.466	44.5051	0.7077
2	922	1.3825	76.3974	0.1787
3	767	1.3691	80.1657	0.1356
4	790	1.4164	67.5064	0.3442
5	687	1.4326	63.9093	0.4468
6	378	1.4467	76.5752	0.2167